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Essays In Asset Pricing And Labor Markets

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Abstract
In the first chapter, "Asset Pricing Implications of Hiring Demographics", I document that U.S. industries that shift their skilled workforce toward young employees exhibit higher expected equity returns. The young-minus-old (YMO) hiring return spread comoves negatively with value-minus-growth while being significantly positive on average. Exposure to the YMO spread accounts for a significant portion of annual momentum profits at the industry level. I find that an adjustment of the skilled workforce toward young employees is associated with greater productivity in new capital inputs of an industry. This motivates a risk-based explanation for the YMO spread, and its interaction with value and momentum. A model of investment and hiring where young and experienced employees are equipped with differential roles in production and investment can account for the empirical findings.

The second chapter, "Risk, Unemployment, and the Stock Market: A Rare-Event-Based Explanation of Labor Market Volatility", co-authored with Jessica A. Wachter, answers the following questions: What is the driving force behind the cyclical behavior of unemployment and vacancies? What is the relation between job-creation incentives of firms and stock market valuations? Our model features time-varying risk, modeled as a small and variable probability of an economic disaster. A high probability implies greater risk and lower future growth, lowering the incentives of firms to invest in hiring. During periods of high risk, stock market valuations are low and unemployment rises. The model thus explains volatility in equity and labor markets, and the relation between the two.

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ABSTRACT

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In the first chapter, "Asset Pricing Implications of Hiring Demographics", I document that U.S. industries that shift their skilled workforce toward young employees exhibit higher expected equity returns. The young-minus-old (YMO) hiring return spread comoves negatively with value-minus-growth while being significantly positive on average. Exposure to the YMO spread accounts for a significant portion of annual momentum profits at the industry level. I find that an adjustment of the skilled workforce toward young employees is associated with greater productivity in new capital inputs of an industry. This motivates a risk-based explanation for the YMO spread, and its interaction with value and momentum. A model of investment and hiring where young and experienced employees are equipped with differential roles in production and investment can account for the empirical findings.

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1.1. Introduction

In the evolving technological environment of the economy, firms look for opportunities to improve their existing operations and to expand by investing in new capital. Two features of the workforce stand out for firms' success in these activities: experience in existing operations and openness to new technologies. Experienced employees offer the ability to improve and expand production processes in place, while the best hires for a firm adopting new technologies may be the ones that are less entrenched into the status quo, and are more adapted to recent advancements in technology. The demographic dimension of hiring activity is therefore likely to be informative about the risks and opportunities embodied in future investments.[1]

In this paper, I investigate the asset pricing implications of hiring demographics. My focus is on the skilled workforce (defined as employees with college or higher degrees) because skilled employees are more likely to be confronted by advancements in technology. I find that U.S. industries that shift their workforce toward young, skilled employees earn higher expected equity returns. The average annualized return differential between high and low young-skilled hiring portfolios from 1965 to 2015 is 4.6%. I call the portfolios of industries tilting toward young and old skilled employees portfolio Y and O, respectively.[2] The portfolio strategy long in portfolio Y and short in portfolio O is labeled YMO. Industries exhibit substantial time-series and cross-sectional variation in whether they tilt their workforce toward young or experienced workers. Therefore, no single industry is responsible for the empirical results.

[1] The importance of labor demographics for economic activity is a recent focus in the literature. Some emphasize the causal impact of demographic changes on the business cycle, and argue for capital-skill complementarity (Jaimovich and Siu (2009) and Jaimovich, Pruitt, and Siu (2013)). In contrast, others focus on the benefits of employing young talent in openness to new technologies, young workers' ability to break away from production methods of the past, and adapt to novel business processes (Acemoglu, Akcigit, and Celik (2014) and Liang, Wang, and Lazear (2014)).

[2] I use the phrases old and experienced interchangeably. In general, "young" refers to recent college graduates and "old" or "experienced" refer to all employees that are not in the young group.

The YMO return spread has an alpha of 5.6% after controlling for Fama and French (1993) factors. It is negatively correlated with the HML (value minus growth) factor, which implies positive comovement between industries that focus on hiring young employees and growth stocks. Because growth stocks have lower returns, unlike stocks in portfolio Y, the HML factor does not explain the average returns of the YMO strategy, and results in a Fama and French (1993) three-factor alpha that is larger than the average YMO spread. Controlling for profitability and investment factors recently proposed by Hou, Xue, and Zhang (2014) and Fama and French (2015) does not alter the results. A well-known feature of the cross-section of industry returns is momentum (Jegadeesh and Titman (1993), Moskowitz and Grinblatt (1999)). The YMO return spread is significantly positively associated with, and helps explain industry momentum (INDMOM) returns.

What is the underlying force responsible for these results? To answer this question, I investigate the interaction between the demographic dimension of hiring and two types of technological progress that are major drivers of economic growth:[3] total factor productivity (TFP), which affects the entire capital stock in place, and investment-specific technology (IST), which is embodied in new capital only.[4] First, the YMO return spread has a significant positive exposure to measures of aggregate IST shocks, while it tends to be negatively associated with TFP shocks.[5] This is in sharp contrast with the HML factor return, which has a positive loading on TFP shocks and a negative loading on IST shocks. The differential

[3]Greenwood, Hercowitz, and Krusell (1997) find that investment-specific technological change played a major role in post-war U.S. economic growth in addition to neutral productivity growth.

[4]I use the terms TFP and disembodied technology as well as IST and embodied technology interchangeably.

[5]The interpretation of these fundamental shocks is particularly suitable for the question studied in this paper as can be seen in the definitions by Berndt (1990) (also used by Kogan, Papanikolaou, and Stoffman (2016)): "Embodied technical progress refers to engineering design and performance advances that can only be embodied in new plant or equipment. To the extent that technical progress is embodied, its effects on costs and production depend critically on the rate of diffusion of the new equipment, which in turn depends on investment and the resulting vintage composition of the surviving capital stock. By contrast, disembodied technical progress refers to advances in knowledge that make more effective use of all inputs, including capital of each surviving vintage (not just the most recent vintage). In its pure form, disembodied technical progress proceeds independently of the vintage structure of the capital stock. The most common example of disembodied technical progress is perhaps the notion of learning curves, in which it has been found that for a wide variety of production processes and products, as cumulative experience and production increase, learning occurs which results in ever decreasing unit costs. Some have called this type of learning process learning by doing, learning through the examples of others, or learning by using."

exposure of YMO and HML returns to macroeconomic shocks offers an explanation for their negative correlation in the time series while making a joint explanation for YMO and HML returns rather challenging. In addition to being positively correlated, YMO and INDMOM returns exhibit similar comovement with aggregate TFP and IST shocks, suggesting that their positive correlation is driven by their exposure to fundamental shocks. Second, using industry-level data on the relative price of investment goods, I show that a shift toward young-skilled employees in hiring activity is a leading indicator of higher technology embodied in new capital formation compared to the rest of the economy over a subsequent medium-term period. This period is also accompanied by higher quantities of investment in capital goods that embody rapid technological progress: equipment, software, and R&D. These patterns are in line with the intuition discussed above: industries facing investment opportunities that embody high levels of technology prefer to populate their skilled workforce with younger employees, while a lower level of embodied technology in new capital is associated with an emphasis on experience in the hiring process.

Motivated by the evidence on the association of hiring demographics with fundamental shocks to technology, I propose a partial equilibrium model of firms where young and old employees have differential roles in production and capital investment. Specifically, I assume that experienced employees are more productive in working with assets in place to capture the benefit of experience in existing operations. Young employees, in contrast, offer an opportunity to reduce capital adjustment costs if the firm is facing higher embodied technology levels in new capital. Therefore, the demographic composition of the workforce has a direct impact on the capital adjustment costs of the firm. The causal chain behind the model mechanism is as follows. A firm faces investment opportunities that embody a high level of technology compared to the rest of the economy. This is characterized by a persistent increase in firm-specific embodied technology consistent with the empirical evidence. Because of the dependence of capital adjustment costs on the composition of labor, the firm optimally decides to hire more young employees.

Firms that desire to adjust most rapidly toward young employees are those most exposed to fluctuations in aggregate embodied technology. Because the adjustment in the composition of labor takes place first, it is a leading indicator of the high-investment period and can therefore serve as a proxy for the conditional exposure to aggregate IST shocks. The model explains the positive average returns for the YMO strategy given a positive market price of risk for aggregate IST shocks. This is consistent with models in which improvements in embodied technology are associated with a decrease in the marginal utility of marginal investors. The average YMO spread constitutes compensation for exposure to technological progress in new capital. In the model, value firms are more exposed to aggregate TFP shocks due to the operating leverage caused by the presence of labor and capital adjustment costs as well as wages that are not very responsive to shocks. Therefore, a positive market price of risk for TFP shocks helps explain the value premium. There is a tension between the impact of IST shocks on average YMO returns and the value premium, because growth opportunities are more positively exposed to aggregate IST shocks compared to assets in place. Hence, a positive value premium arises because the positive impact of exposure to TFP shocks dominates the negative impact of exposure to IST shocks.

This paper is closely related to three strands of literature. First, the relation between labor markets and asset prices is a recent focus in finance. Belo, Lin, and Bazdresch (2014) document that firms with low hiring rates have higher expected returns and explain their findings in a partial equilibrium model using shocks to adjustment costs of the workforce. Belo, Lin, Li, and Zhao (2016) observe that the hiring return spread is largely driven by skilled workers and show that this can be explained assuming costlier adjustment for skilled workers. Ochoa (2013) also argues for costlier adjustment for skilled labor and studies the relation between volatility risk and labor frictions. Kuehn, Simutin, and Wang (2014) show that firms have differential exposures to fluctuations in the aggregate matching efficiency in the labor market contributing to explanations of cross-sectional stock return spreads. Donangelo (2014) studies the impact of labor mobility on asset prices, while Zhang (2015) focuses on the implications of labor-saving technologies for asset prices. Donangelo, Gourio, and Palacios (2015) and Favilukis and Lin (2014) study the impact of operating leverage induced by labor costs on asset prices. The present paper explores a novel dimension of the workforce on asset returns, namely, the demographic structure of hiring dynamics. In the empirical analysis, I show that the relation between hiring demographics and equity returns is different from documented cross-sectional patterns related to hiring and investment. Further empirical evidence on the relation between hiring demographics and technological progress, which I use to construct the model, is consistent with the mechanism driving the asset pricing results.

Second, investment-specific technological progress has become an important feature of economic models starting with Greenwood, Hercowitz, and Krusell (1997). This type of fluctuations in technology has been adopted in recent finance literature. Papanikolaou (2011) studies the implications of IST shocks on asset prices in a two-sector general equilibrium model, while Kogan and Papanikolaou (2013) and Kogan and Papanikolaou (2014) study the implications of IST shocks in partial-equilibrium models. Garlappi and Song (2016) estimate a positive price of risk for IST shocks using a long sample of portfolio returns and relative price of investment in the data. In this paper, I present evidence on the interaction between the implications of hiring demographics and IST shocks, and provide conditions under which the exposure to IST shocks can help explain the positive and significant return spread between industries focusing on young versus experienced employees in hiring. The positive association between industry momentum and the YMO spread is related to Li (2014) who builds a model with investment commitment to explain momentum profits based on their positive exposure to IST shocks. In the model presented in my paper, firms that face favorable IST shocks optimally decide to change the composition of the workforce first, and then increase investment which gives rise to persistent exposure to aggregate IST shocks for winner firms.

Finally, the economic implications of the demographic composition of the workforce is an active area of research in macroeconomics. Jaimovich and Siu (2009) study the implications of the changing labor demographics in the U.S. for business cycle volatility. Jaimovich, Pruitt, and Siu (2013) focus on the differential fluctuations of hours experienced by young and old employees, and argue for capital-experience complementarity. I use this insight to model the differential role of young and old employees in production. Acemoglu, Akcigit, and Celik (2014) find that firms that plan to intensively engage in innovative activity tend to hire younger managers. While I focus on the entire skilled workforce, and a broader definition of technological progress and investment, the causal chain in this paper that young employees sort to firms that have future expectations of high-technology investments is in line with their findings. These papers focus on the role of young and old employees in production like the present paper, but do not study asset pricing implications. Gârleanu, Kogan, and Panageas (2012) study the implications of displacement risk induced by innovation that experienced agents face for the value premium. In their model, growth firms and future generations are beneficiaries of innovation, and innovation constitutes a negative shock to existing agents' human capital. Therefore, growth firms become a hedge against existing agents' income risk. In this paper, I view young and old employees as differential factors of production rather than focusing on their portfolio choice, and consider the firm hiring decisions that depend on the growth opportunities they face.

The paper is organized as follows: Section 1.2 presents the data, describes the empirical analysis of portfolio returns and their interaction with technology shocks. Section 2.3 presents the model and shows the results from the calibration exercise. Section 1.4 concludes.

1.2. Empirical Analysis

In this section, I present and discuss the empirical evidence on the relation of hiring demographics and the cross-section of stock returns. Section 1.2.1 presents the data sources used for the main analysis. Section 1.2.2 describes the formation of portfolios and portfolio characteristics. Section 1.2.3 starts with the presentation of portfolio returns and analyzes them in the context of factor models, robustness checks, and interactions with other features of the cross-section of returns. Section 1.2.4 presents evidence on the relation of portfolio returns resulting from hiring policy to momentum profits. Section 1.2.5 provides evidence on the interaction of the demographics of hiring with macroeconomic shocks and investment which will motivate the model in Section 2.3.

1.2.1. Data

The main source for labor market data is the U.S. labor file of the KLEMS data set constructed by Jorgenson, Ho, and Samuels (2012).[6] The data set provides the number of employees and compensation per employee at an annual frequency for U.S. industries. The industry classification follows the international SIC system. All variables are available by education level, age group, and a decomposition into employees and the self-employed. The labor market variables in the KLEMS data set are calculated using the March supplements of the Current Population Survey (CPS) and covers the period from 1947 to 2010. I confirm that the finalized data are closely replicable using the CPS files and extend all variables until 2015. The analysis in this paper uses the series for private sectors excluding agriculture.[7] This results in a data set consisting of 27 industries, which are listed in Table 1.1.

I use stock returns from the Center for Research in Security Prices (CRSP) and accounting information from the annual files of the CRSP/Compustat Merged dataset. To match the stock return and accounting data with the labor market data, I use a mapping between the standard industrial classification codes (SIC) from the CRSP/Compustat Merged dataset and the international SIC codes from the United Nations Statistics Division.

1.2.2. Portfolios

The focus of this paper is the cross-sectional variation in the demographic dimension of hiring activity and its interaction with the differential growth opportunities and technologies faced by firms. For this purpose, I exclusively use data on the skilled workforce as skilled employees are more likely to be confronted with technological progress. Skilled workforce

[6] KLEMS stands for capital, labor, energy, materials, and services.
[7] Specifically, I exclude the public administration and defense industries, education, and private households with employed persons.

is defined as requiring college completion or higher degrees as in Krusell, Ohanian, Ríos-Rull, and Violante (2000). The key variable capturing the demographic focus of hiring at the industry level is given by $\omega_t = \log(l_t^y/l_{t-1}^y) - \log(l_t^o/l_{t-1}^o)$, where l_t^y is the number of young employees and l_t^o is the number of old employees in year t.[8] This corresponds to the difference between the hiring rates for the young and old workforce.[9]

I use value-weighted monthly stock returns for each industry. To study the link between hiring activity and expected returns, I match ω_t with monthly returns from January to December of year $t+1$. This allows for a gap between the realization of the sorting variable and returns as in Fama and French (1992). To construct portfolios, I sort industries based on ω every year. The young (Y) portfolio consists of five industries with the highest values of ω, namely the industries that shift their skilled workforce toward younger employees the strongest. Analogously, the old (O) portfolio contains the five industries with the lowest ω values. The remaining industries are grouped into the medium (M) portfolio. For the main analysis, I use the specification with three portfolios and the age of 29 for the classification of employees into young and old groups. Most accounting variables related to investment and hiring at the firm level are available starting from 1965. The KLEMS data set also seems more reliable from the 1960s, as there is almost no inertia in the time series of variables in this period. The availability and reliability of data results in a final dataset of 600 months from 1965 to 2015. The robustness of the results to perturbations from the baseline case is discussed in Section 1.2.3.6.

Table 1.2 summarizes some key characteristics of the Y, M, and O portfolios. The average change in the young-to-old ratio, ω, is 5%, 0% and -6% for the Y, M, and O portfolios, respectively. The average growth of the number of young employees is 8% in portfolio Y while the growth of old employees is only 3%.[10] The average shares of portfolios Y and O in

[8] See Appendix A1.2 for implications of the level versus changes in the demographic composition of labor.

[9] Another way to interpret ω is the change in the ratio of young to old employees in the industry.

[10] Note that the differences in ω are not necessarily driven by firing of young or old employees. In the U.S., about 2% of employees quit their job every month. Therefore, a differential focus in hiring on the young and old is sufficient to generate the observed differences in ω across portfolios.

aggregate market capitalization are similar with 18% for the Y and 17% for the O portfolio. The symmetric distribution of average market shares is a result of high turnover: although industries have different average market size shares, there is no industry that dominates a portfolio and drives the results.

Stocks in portfolio Y have a lower average book-to-market ratio (B/M) (0.65) than stocks in portfolio O (0.72). Although the relation is not monotonic with an average B/M if 0.61 for portfolio M, portfolio Y exhibits more growth-like behavior than portfolio O. However, the spread in average B/M is small compared to sorts on B/M itself, where the lowest-quintile portfolio can have an average B/M as low as 0.25 and the highest-quintile portfolio has an average B/M of 1.59.

I also investigate whether adjustments to the demographic composition of the workforce are associated with expansions or contractions in the quantity of the workforce and physical capital, both of which have been found to have a significant impact on the cross-section of equity returns. As Table 1.2 shows, there is no significant pattern in those quantities, just as there is none in profitability. An important feature of the data is thus that changes in the demographic composition of the skilled workforce are not associated with significant changes for industries at the extensive margin of capital and labor.

1.2.3. Demographics of Hiring and Stock Returns

1.2.3.1. Portfolio returns

What do adjustments to the workforce demographics imply for the cross-section of stock returns? To answer this question, I compute the monthly value-weighted stock returns of portfolios Y, M, and O from January 1966 to December 2015. Panel A of Table 1.3 shows that the average annualized excess return of portfolio Y is 9.17%, while it is 4.52% for portfolio O. The return spread between portfolios Y and O (called YMO hereafter) is 4.64% on average and statistically significant with a t-statistic of 3.09.[11] The Sharpe ratios

[11] All t-statistics are based on Newey-West standard errors with six lags in monthly data unless otherwise stated.

of portfolios are also monotonic with 0.52 for portfolio Y and 0.26 for portfolio O.

Panel B and Panel C of Table 1.3 report results from CAPM and Fama and French (1993) three-factor (FF-3) regressions of portfolio returns. CAPM provides little explanatory power for the YMO portfolio returns, with an R^2 of 2%, yet it yields a statistically significant coefficient of 0.10 on market excess returns. However, the market exposure is too small to explain the average YMO return, resulting in a CAPM alpha of 4.18%. The FF-3 regressions deliver a striking result: while the explanatory power of the FF-3 model is higher than that of CAPM for the variation in the YMO portfolio returns with an R^2 of 8%, the FF-3 alpha is larger than the average return spread, namely 5.56% with a t-statistic of 3.64. This stems from a significant negative loading of -0.30 on the value-minus-growth (HML) factor. The returns of portfolio Y comove positively with value and negatively with growth stocks, while portfolio O exhibits the opposite behavior. Figure 1.30 plots the 5-year average monthly YMO returns and the corresponding FF-3 alphas. The YMO returns is positive in the vast majority of 5-year periods, and is high in both the earlier and the later subsamples.

The conclusion from the results in Table 1.3 is not only the failure of the unconditional CAPM and FF-3 models to explain the YMO return spread but also the spread's interaction with the well-studied value premium, namely that value firms have significantly higher average returns than growth firms. Portfolio Y has high average returns despite more "growth-like" behavior in terms of its factor loadings, while growth (low B/M) firms have lower returns. This observation is key for the choice of model ingredients presented in Section 2.3 to explain the YMO spread consistent with the empirical evidence. The factor regressions thus provide valuable information about the set of potential risk-based explanations for the YMO spread.[12]

1.2.3.2. Alternative factor models

Recent literature has modified the FF-3 model by factors related to investment and profitability. Hou, Xue, and Zhang (2014) propose a four-factor model motivated by a simple

[12]See Table 1.36 for results from rolling factor regressions.

version of the q-theory, which predicts a negative relation between investment rates, and a positive relation between profitability and expected returns. As shown in Panel A of Table 1.4, the implications of the q-factor model for the YMO return spread are similar to those of the FF-3 model. The q-factor alpha is 5.72%, and the loading of the YMO spread on the investment factor, which has a correlation of 69% with the HML factor of the FF-3 model, is negative. Fama and French (2015) (FF-5) extend the FF-3 model by the investment and profitability factors motivated by the fact that the FF-3 model does not explain the positive average returns of strategies based on investment and profitability. Panel B of Table 1.4 shows that the FF-5 model delivers results similar to those of FF-3. Specifically, the loadings of the YMO return on profitability and investment factors are small and insignificant, while the negative loading on HML remains significant and its magnitude does not change significantly. The FF-5 alpha of the YMO spread is 6.16% with a t-statistic of 3.64.

1.2.3.3. Firm-level predictability

Next, I investigate the predictive ability of ω at the firm level. To do this, I assign the industry-level value for ω to all firms in the same industry every year. I use investment rates (I/K), hiring rates (H/N), and B/M from accounting data to assess the marginal predictability of ω. Table 1.5 shows that ω has predictive power for annual stock returns: a 10 percentage point increase in ω (which is close to a one standard deviation increase based on the unconditional volatility of ω at the industry level) is associated with a 1.5 percentage point increase in the firm's annual stock return. The magnitude of this effect does not change significantly when controlling for I/K, H/N, and B/M.

1.2.3.4. Double sorts

Table 1.6 reports results from double sorts based on ω and other characteristics that are known to predict returns in the cross-section of stocks. To do this, I maintain the classification of industries into portfolios Y, M, and O as in the baseline analysis and sort stocks based on another characteristic within these portfolios using NYSE breakpoints.[13]

[13] Two-way sorts and sorts first on another characteristic and then on ω deliver very similar results.

To summarize, the YMO return spread is positive in all double sorts, while its magnitude and statistical significance varies. The YMO spread is larger among growth (low B/M) stocks (4.66%) than among value (high B/M) stocks (2.57%). The value premium is large in all portfolios Y, M, and O, while it is statistically significant in M and O.[14] Unlike many cross-sectional return dispersions, the YMO spread is not concentrated in small stocks. The YMO spread is also largest among low hiring and investment portfolios, while it is large and significant among medium portfolios of these categories as well. High investment and high hiring portfolios also have positive YMO spreads, while their statistical significance is low. The FF-3 factor model has explanatory power for book-to-market, size, investment, and employment growth sorts while it does not for YMO in double sorts. Overall, the YMO spread is positive among various sets of stocks grouped by characteristics known to predict returns. It is strongest among the growth, non-micro cap, low to moderate investment and hiring groups.

1.2.3.5. Exposure to YMO

As discussed in Section 1.2.2, portfolios are not dominated by certain industries. To summarize the information about industries' exposure, I regress 49 industry excess returns on the YMO return and report five industries with the highest and lowest exposures in Table 1.7.[15] High exposure industries tend to be in high-technology areas such as computer software and hardware development, as well as measuring, control, and electronic equipment. While the machinery, shipbuilding and railroad equipment, and petroleum industries are among the most exposed in the earlier half of the sample (1966 - 1989), high-technology industries are the most exposed in the second half of the sample (1990 - 2015). The focus on young and skilled workers in hiring activity is thus concentrated in areas of rapid technological progress, especially over the last 25 years. Industries with the lowest exposure to YMO, such as plastic products, entertainment, food, and accommodations, are less likely

[14] The presence of a value premium in portfolios Y, M, and O is consistent with Cohen, Polk, and Vuolteenaho (2003) who find that the book-to-market effect in returns is mostly an intra-industry effect.

[15] I use 49 industry returns from Kenneth French's website.

to depend on ongoing technological progress.[16]

1.2.3.6. Robustness checks

To check the robustness of the findings, I conduct several robustness tests and report the results in Table 1.8. I split the sample into two equally sized periods, taking December 1989 as the last observation of the first subsample. The average YMO spread in the first and second halves of the subsample is 5.41% and 4.44% with t-statistics of 2.30 and 2.39, respectively. Most studies omit financial firms because the characteristics of financial firms, such as investment, have a different economic content compared to regular firms. Omitting the financial and real estate industries results in an average YMO spread of 3.96% with a t-statistic of 2.60. There is a positive relation between R&D expenditures and stock returns among firms that report positive R&D expenditures (Chan, Lakonishok, and Sougiannis (2001), Li (2011)). This relation is particularly relevant for an interpretation based on exposure to technological progress because R&D activities embody new technologies by definition. I exclude all firms that report positive R&D expenditures in Compustat. The YMO spread after this omission is 3.48% and statistically significant, which implies that the YMO spread is not entirely driven by cross-sectional differences related to high R&D industries but holds more generally for all industries. Finally, I set the age for classification into young and old to 35 and still obtain a YMO return spread of 3.71%. Another concern is the definition of skill. For main results, I defined skilled employees as those who hold at least a college degree. However, a college degree in 1960's represents a better place in the skill distribution of the workforce than it does today. Therefore, I split the education distribution into its upper and lower half every year such that, say, a high school graduate is in the skilled group in 1960's, but not in 2000's. Table 1.8 shows that main results remain unchanged using this definition of skill. A notable common feature of the YMO spread in all robustness checks is its negative loading on the HML factor as shown in Panel B of Table

[16]The average returns of five highest-exposure industries is not statistically different from the ones with lowest exposure to YMO, or the aggregate market return. Thus, time variation in portfolios is important to capture the positive average YMO return.

1.8. This results in FF-5 alphas that are larger than the YMO spread in all cases.

Table 1.9 shows the benchmark results for five portfolios formed on ω. For this exercise, I keep the Y and O portfolios the same as in the baseline case and split portfolio M into portfolios 2, 3, and 4 containing five, seven, and five industries, respectively. The excess returns, CAPM, and FF-3 alphas of the five portfolios monotonically increase in ω, while the differences in the average returns of portfolios 2, 3, and 4 are not statistically significant. Finally, I investigate the behavior of portfolio returns at the annual frequency and report the results in Table 1.10. The results are similar to the case using monthly returns (Table 1.3). Specifically, the CAPM and FF-3 alphas are positive and significant despite the lower number of observations. The loading of the YMO spread on the HML factor in annual data is significantly negative and slightly larger than in the monthly data in absolute value.

1.2.4. Relation to industry momentum

A striking feature of the cross-section of returns is persistence, commonly referred to as momentum. Jegadeesh and Titman (1993) document that stocks with high recent performance (winners) continue to have higher returns compared to stocks with low recent returns (losers). The literature has investigated the properties of momentum for stocks and other asset classes extensively, and most existing theoretical explanations are behavioral, such as underreaction to information.[17]

The YMO spread has a correlation of 16% with the UMD factor at both the monthly and annual frequency.[18] The correlation is particularly high when the bursting of the tech bubble and the Great Recession are excluded. Specifically, it is 34% at the monthly frequency and 58% at the annual frequency in the sample from 1966 to 1999. This is because of the negative comovement between YMO and UMD during "momentum crashes," namely prolonged periods of low momentum performance following large market downturns as studied in Daniel and Moskowitz (2016). Figure 1.2 demonstrates this point by plotting

[17]See Jegadeesh and Titman (2011) for an overview.
[18]The UMD factor is available from Kenneth French's website.

the annual dynamics of normalized YMO and UMD returns in the upper panel and the three-year average dynamics in the lower panel. Momentum returns and the YMO spread closely track each other, with the most notable exception of the Great Recession period.

Despite their high degree of comovement, the YMO spread does not provide a full explanation for momentum profits captured by UMD when used as a factor. The average UMD return is 8.57% (11.92%) in the period from 1966 to 2015 (1966 to 1999). When regressed on the YMO spread, it still has an alpha of 7.55% (9.31%). However, the direct comparison of YMO and UMD may be misleading for two reasons. First, the UMD factor is constructed using portfolios rebalanced at the monthly frequency (based on prior 2- to 12-month returns), while the YMO spread is computed rebalancing portfolios at annual frequency because of the availability of labor market data. Second, UMD is constructed using individual stock price momentum, while the YMO spread is computed from industry returns as described in Section 1.2.2. The first point can be addressed by changing the frequency of portfolio rebalancing and is related to the persistence structure of momentum profits. Novy-Marx (2012) shows that strategies based on past 6- to 12-month returns deliver higher average returns compared to the profits of strategies based on very recent performance in the past two to six months. The second point is particularly interesting in the context of momentum profits, as Moskowitz and Grinblatt (1999) document that high momentum returns can be achieved at the industry level, explaining a large fraction of momentum profits at the individual stock level.

Addressing these points may help project momentum profits to a comparable space as the YMO spread. Therefore, I analyze industry momentum (INDMOM) portfolios with annual rebalancing and report the results in Table 1.11. First, I use the 30 industry portfolio returns from Kenneth French's website (Panel A). In light of Novy-Marx (2012)'s findings, I sort industries based on returns from January to July of year t and compute returns in year $t+1$ for the baseline analysis. I also analyze INDMOM profits based on returns from July to December of year t and compute quantities for the samples from both 1966 to 2015 and 1966 to 1999.[19] Five winner industries outperform five loser industries by an average return of 4.48%, with statistically significant CAPM and FF-3 alphas of 3.43% and 5.13%, respectively. The correlation between YMO and INDMOM is 33%, which is higher than the correlation of 16% with UMD. As shown in Figure 1.3, the increase in the correlation is primarily driven by the large crash in UMD during the Great Recession that is absent in INDMOM and YMO. To understand whether industry momentum accounts for the comovement between UMD and YMO, I regress UMD on INDMOM (which delivers an R^2 of 13%) and compute the OLS residuals. The residual of UMD after this orthogonalization has a correlation of only 4% with YMO, which suggests that the common component of YMO and UMD is primarily driven by the industry component of momentum profits.

While industry momentum has significant CAPM and FF-3 alphas, the market return and the YMO spread account for about half of it, leading to an alpha of 2.28% with a t-statistic of 1.50. Table 1.11 also shows that the difference between the average INDMOM returns and alphas after the inclusion of YMO as a factor in time series regressions is even larger in the sample from 1966 to 1999 (which is close to the sample used by Moskowitz and Grinblatt (1999) to study industry momentum) and when the industry classification follows the international SIC divisions. The YMO spread, which is constructed using information on the hiring policies of industries along the demographic dimension, thus provides a potential explanation for INDMOM. This result occurs when INDMOM is computed using the same frequency and granularity of information as the computation of the YMO spread. Winner industries behave similarly to industries hiring young-skilled employees, while losers tend to favor experienced workers. I leave further investigation of how to make YMO more operational to test explanations of momentum profits for future research.

[19] I repeat the analysis using the international SIC classification used to construct the YMO returns and report results in Panel B of Table 1.11.

1.2.5. Relation to macroeconomic shocks and investment

This section provides evidence on the relation of portfolio returns on fundamental shocks. Section 1.2.5.1 assesses the exposures of YMO, HML, and INDMOM returns to aggregate TFP and IST shocks. Section 1.2.5.2 presents an empirical relation between the demographics of hiring and IST shocks in the cross-section of industries.

1.2.5.1. Aggregate shocks

The driving force in most investment-based models of the cross-section of returns is differences in exposure to total factor productivity (TFP) (e.g., Gomes, Kogan, and Zhang (2003), Zhang (2005)). A recent strand of literature emphasizes the role of investment-specific technology (IST) shocks as a potential source of risk driving cross-sectional differences in expected returns (e.g., Papanikolaou (2011), Kogan and Papanikolaou (2013), Kogan and Papanikolaou (2014)). While TFP shocks affect the productivity of all assets in place, IST shocks are embodied in new capital goods. I summarize the evidence on the exposure of the YMO spread in this section and use it to construct the model in Section 2.3.

I use annual data on TFP from Fernald (2014), available from the Federal Reserve Bank of San Francisco website, for TFP shocks (Δa). Innovations in the price of investment goods relative to consumption goods provide a proxy for IST shocks (Greenwood, Hercowitz, and Krusell (1997)). Specifically, the relative price of new equipment exhibits a downward trend in the postwar U.S. data. This represents the expanding investment opportunity set in the economy driven by the technological progress in new capital goods. Firms profit from and expose themselves to such technological progress to the extent that they invest and form new capital (see Section 2.3 for a more detailed discussion). I use the inverse of the quality-adjusted relative price of equipment constructed by Israelsen (2010) to compute the first measure of IST shocks (Δz). The second measure of IST shocks is the equity return differential between investment and consumption goods-producing sectors in the

U.S. economy. This return differential serves as a proxy for investment shocks under the assumption of a two-sector model where the consumption sector buys investment goods from the investment goods sector to expand capital (Papanikolaou (2011)). While a perfect empirical classification of firms into investment and consumption goods producers is difficult, as most industries produce both types of goods, Gomes, Kogan, and Yogo (2009) propose a methodology based on the majority of sales for every industry, which I use to compute the return differential between the investment and consumption sectors (R_{imc}).

Table 1.12 reports results from time series regressions of YMO, HML, and INDMOM returns on proxies of TFP and IST shocks, which I normalize to have unit standard deviation. I consider three specifications. The first one computes the return exposures to Δa and Δz. The YMO spread has a negative loading on Δa, which is large but not statistically significant, while it has a positive and significant loading on Δz. Specifically, a one standard deviation shock to Δz leads to a 4% higher contemporaneous YMO spread on average. The loading of the HML return on Δa is positive and significant, while it is negative and not significantly different from zero for Δz. Next, I replace Δz by R_{imc}. This increases the joint explanatory power of TFP and IST shock proxies for all three returns considered in this section. The negative loading of the YMO return on Δa does not change significantly in magnitude compared to the first specification, but it becomes statistically significant. The YMO return has a significantly positive loading on R_{imc}, as it does on Δz. While the HML return has a positive and significant loading on Δa, its loading on R_{imc} as a proxy for IST shocks is negative and highly significant. A one standard deviation increase in R_{imc} corresponds to a contemporaneous 2% drop in the annual HML return.

The exposure of returns to macroeconomic shocks sheds some light on the comovement between YMO and HML discussed in the previous sections. The opposite loadings of the YMO and HML on fundamental shocks can explain the negative comovement between these two long-short portfolio returns. At the same time, the significant and opposite loadings on macroeconomic shocks are informative about potential joint explanations of positive average returns for YMO and HML strategies. I use these results to discipline the model in Section 2.3 that can explain the positive expected returns of YMO and HML, while being consistent with the association of returns with macroeconomic shocks.

Finally, INDMOM has a negative loading on Δa, while its exposure to Δz is not statistically different from zero. The loadings of INDMOM on Δa and R_{imc} are similar to those of YMO. The positive comovement of YMO and INDMOM is also consistent with their loadings on TFP and IST shocks, especially when R_{imc} is used as the proxy for IST shocks.

The last specification uses the aggregate excess market return (R_m) and R_{imc} as the right-hand variables. The loadings of YMO, HML, and INDMOM on R_m are not statistically different from zero, while the loadings on R_{imc} are very close to the second specification where I include Δa instead of R_m.

1.2.5.2. IST shocks and investment at the industry level

The nature of investment goods that industries need is different and varies over time, so it is natural to expect that there is heterogeneity in the technology levels embodied in new capital across industries. Is there any association between investment opportunities and the demographic dimension of hiring policy? In this section, I provide some direct evidence that answers this question beyond the return-based evidence discussed in Section 1.2.5.1. I use the inverse of the relative price of investment at the industry level as the proxy for the embodied technology level. The KLEMS data set provides quality-adjusted price indices for capital services at the industry level and annual frequency. I divide these by the consumption deflator to compute the relative price of investment at the industry level.[20] The price indices in KLEMS include all investments, while the aggregate index from Israelsen (2010) used in Section 1.2.5.1 includes only equipment investments, namely investment goods with the fastest technological progress. Despite this caveat, the relative price of investment computed from KLEMS falls steadily in the postwar period.[21] It also

[20] I use the consumption deflator data from the Federal Reserve Bank of St. Louis (FRED).

[21] Unlike equipment and software, the relative price of structure investment does not decrease in the postwar period (Jermann (2010)). Considering the fact that, a large portion of gross private investment is

preserves the interaction of IST shocks with returns as reported in Section 1.2.5.1. Aggregate IST shocks computed from KLEMS data have a correlation of -29% with HML and 33% with YMO (compared to -5% and 22% using the equipment price data from Israelsen (2010) and -62% and 47% using R_{imc}).

For each of the 27 industries listed in Table 1.1, I compute the inverse of the relative price of investment (called industry IST level hereafter). To compute the IST level for portfolios Y, M, and O, I weight industry IST levels using the quantity of total investment for each industry. I normalize the portfolio IST levels to one four years before portfolio formation and track the pattern of portfolio IST levels until nine years after portfolio formation. Figure 1.4 illustrates the average dynamics of embodied technology from this exercise at the portfolio level. The average IST levels of portfolios are similar before the portfolio formation year. From the portfolio formation year onwards, the IST level of industries in portfolio Y start to deviate upward, while it deviates downward for portfolio O relative to portfolio M. In other words, industries that shift their skilled workforce toward young employees experience a contemporaneous and subsequent rise in the embodied technology level in new capital goods. The divergence of portfolios continues until about five years after portfolio formation, when portfolio Y experiences a 3.5% increase in IST level while portfolio O's IST level drops by 4% relative to portfolio M. The difference between the growth of IST technology of portfolios Y and O in the portfolio formation year has a t-statistic of 2.01, while the average difference in cumulative growth rates in the five years upon portfolio formation has a t-statistic of 1.81.[22]

in structures, the inclusion of structures makes the decline in the relative price of investment from KLEMS data less pronounced compared to equipment only. The growth rate of the aggregate IST level is 0.88% in the KLEMS data with an annual volatility of 3.2%.

[22]The exercise that results in Figure 1.4 treats all industries as consumption goods producers in a two-sector economy such as the one in Papanikolaou (2011). However, some industries have a higher share of their output sold as investment goods. If the relative prices of investment and output of an industry drop at the same time, the industry may not have a net profit from technological progress. To address this issue, I use the price indices of value added for each industry (instead of the consumption deflator) to compute the relative price of investment at the industry level. The resulting average IST levels are plotted in Figure 1.1. While the IST levels are less stable before portfolio formation, one can observe a divergence in the IST levels of portfolios Y and O upon portfolio formation similar to that shown in Figure 1.4.

Table 1.13 provides further evidence that demographic shifts predict investment growth in equipment, software, and R&D. A one standard deviation increase in ω predicts 6.61 percentage points higher investment growth over the last year, and 14.75 percentage points higher investment growth over the last three years at the industry level. As shown in Table 1.14, however, demographic shifts are not associated with future investment in structures.[23] These results are robust to controlling for past investment rates (Table 1.23), and supports more directly the idea that industries hire a younger skilled workforce, when they are expected to increase investments in types of capital that embody new technologies.

The association between a focus on young, skilled employees in hiring policy and a period of higher embodied technology is informative about the relation between hiring demographics, risks, and investment opportunities faced by industries. The pattern depicted in Figure 1.4 can arise because of an acceleration in the embodied technology in the types of capital that an industry invests in. For instance, an industry may rely heavily on the usage of computer and software, which constitute types of capital with rapid technological progress. An acceleration in the decline of the relative prices of computer and software results in an increase in the embodied technology levels, as shown for portfolio Y in Figure 1.4. Another possibility is that young and skilled hiring is associated with a shift in investment opportunities toward types of capital where technological progress is faster. Even if there is no change in the aggregate embodied technologies of, say, structures and equipment, an industry may enter a period of modernization in equipment, and the competitive forces in the industry may lead to higher investment in equipment, increasing the observed embodied technology in new capital. Finally, these two mechanisms can reinforce each other. Fast technological progress in new capital goods lower the relative price of investment goods for an industry. Lower prices for new capital goods can incentivize higher investment because of a substitution effect, and firms may also need to invest in new capital to keep up with the industry-wide technological progress. Both of these forces result in an increase in the

[23]The positive relation between demographic shifts and investment in structures is completely subsumed by year fixed effects. This is because young-skilled hiring in the aggregate economy is more procyclical than old, and therefore associated with aggregate investment growth.

observed embodied technology levels for an industry.

While it is not possible to disentangle the channels affecting the relative price of investment completely, I investigate the presence of the effect on the quantity of investment by repeating the same exercise as illustrated in Figure 1.4 for the quantity of investment in equipment, software, and R&D at the portfolio level and plot the results in Figure 1.5. Industries in portfolio Y start to increase investment after adjusting workforce toward young, skilled employees. This increase takes about three years on average. This is a confirmation that higher embodied technology levels for portfolio Y are also associated with an increase in the quantity of investment in areas where technological progress is prevalent. Furthermore, the association of demographics shifts with future investments tend to operate through the investment shock channel. Table 1.15 shows that the positive association between future investment growth and current demographic shifts is largely attributable to the interaction of the quantity of investment with investment shocks. A significant portion of the loading of current young-old hiring differential on investment growth over the next three years is explained by an interaction term in the embodied technology level of investments over the next three years.[24] This can be interpreted as follows: the composition of the skilled workforce shifts toward young people when high investment is expected, especially when the expected investments embody a higher productivity level. Therefore, the shift of demographic composition toward young employees serves as an early indicator of exposure to productivity risk embodied in future vintages of capital.[25]

1.3. Model

This section presents a partial equilibrium model where young and old employees are differential inputs for firms in terms of their role in production and capital investment. Section 1.3.1 introduces the firm production technology, capital and labor adjustment costs. The

[24]Table 1.26 repeats this exercise with TFP shocks. While TFP shocks have no significant association with demographic shifts, the investment-w relation is weaker when industry-level TFP is high.

[25]See Table 1.31 for statistics about firm entry and exit in the industries grouped by portfolio Y, M, and O.

roles of labor demographics are also presented in this section. Section 1.3.2 describes the stochastic processes driving the economy, and Section 1.3.3 specifies wages and the stochastic discount factor. Section 1.3.4 describes the firm's problem. The model calibration is presented in Section 1.3.5 followed by asset pricing results in Section 2.3.4. Finally, Section 1.3.7 discusses some extensions of the baseline model.

1.3.1. Firm Technology

There is a large number of ex-ante identical firms in the economy that produce a homogeneous good. In this section, I describe the technology of a single firm that makes investment and hiring decisions.[26]

The firm produces output y_t using capital and labor inputs, k_t and n_t, according to the following production function:

$$y_t = u_t a_t k_t^{\alpha_k} n_t^{\alpha_n}, \tag{1.1}$$

where a_t is the aggregate productivity (TFP), which is identical for all firms, and u_t denotes firm-specific productivity. Aggregate and firm-specific productivity determine the firm's disembodied technology level, namely the productivity of all assets in place. α_k and α_n control the sensitivity of production to capital and labor. I assume $\alpha_k + \alpha_n < 1$, which implies decreasing returns to scale at the firm level.

The labor input of the firm is given by

$$n_t = e_y \, l_t^y + e_o \, l_t^o, \tag{1.2}$$

where l_t^y is the number of young employees and l_t^o is the number of old employees. Each young and old employee provides the firm with efficiency units of e_y and e_o, respectively. Given the efficiency units, the inputs by young and old employees are perfectly substitutable. In the quantitative assessment of the model, I assume 0 ¡ e_y ¡ e_o, namely that an old employee

[26]I do not use firm subscripts, as all firms in the economy operate according to the same technology.

is more productive in the existing operations of the firm using assets in place. This captures the fact that old employees are more experienced in working with the capital that has been installed in the past.[27]

The law of motion for the firm's capital is given by

$$k_{t+1} = (1 - \delta)\, k_t + i_t z_t, \tag{1.3}$$

where δ is the depreciation rate per period. The firm expands capital through investment expenditures i_t. The investment-specific technology (IST) level z_t determines how much effective capital the firm can build per unit investment expenditure. The IST level is isomorphic to vintage-specific productivity and is embodied in new capital built through investment. I assume that the embodied technology is given by

$$z_t = \tilde{z}_t\, z_t^a, \tag{1.4}$$

where $\tilde{z}_t$ is the firm-specific component and z_t^a is the aggregate IST level, which is identical for all firms.[28] For each firm, I assume $\mathbb{E}\left[\tilde{z}_t\right] = 1$, while z_t^a grows over time.[29] This implies that the embodied technology at the firm level fluctuates around the aggregate embodied technology level. Depending on whether the firm-specific component is above or below one, the firm faces an embodied technology that is higher or lower than the average firm in the economy.

One can interpret the firm-specific component $\tilde{z}_t$ as the productivity of firm investment opportunities relative to the rest of the economy. A firm with a high level of $\tilde{z}_t$ faces a technology level in investment opportunities that is less likely to have been experienced by the average firm in the economy. A low level of $\tilde{z}_t$, in contrast, represents a technology level

[27] Jaimovich, Pruitt, and Siu (2013) also view young and old employees as differential factors of production. Their model of the production function assumes a lower degree of complementarity with capital for hours provided by young employees compared to old employees. I opt for the simple specification of perfect substitutability yet differential efficiency units for the purposes of this paper.

[28] In recent work, Dou (2016) studies the impact of uncertainty in firm-specific IST shocks on asset prices.

[29] See Section 1.3.2 for the stochastic processes of technology variables.

that is more likely to have been experienced by the average firm in new capital formation.

Hiring decisions in the present model are intertemporal, as is capital investment. The laws of motion for the quantity of young and old employees are given by

$$l_{t+1}^{y} = (1 - s)\, l_t^y + h_t^y, \tag{1.5}$$

and

$$l_{t+1}^{o} = (1 - s)\, l_t^o + h_t^o, \tag{1.6}$$

where s is the separation rate per period. The quantities of young and old labor hiring are given by h_t^y and h_t^o, respectively. The quantity of hiring can be negative, which occurs in cases where firms want to lower the number of employees more than implied by the separation rate s.

Hiring and firing are costly processes for various reasons: new employees may need training, hiring involves vacancy advertising and a search for new employees, and separations result in the loss of firm-specific human capital that new employees need to accumulate. I assume the following quadratic adjustment cost function for labor to capture these features of the hiring process:

$$\Psi_t^n = c_n \left(\frac{|h_t^y| + |h_t^o|}{n_t} \right)^2 n_t, \tag{1.7}$$

where c_n is a constant. Labor adjustment costs are quadratic in a measure of labor turnover and scale with the size of the labor input of the firm.

I also assume the presence of capital adjustment costs given by

$$\Psi_t^k = c_k (1 + \Psi_t^z)\, \bar{\Psi}_t^k, \tag{1.8}$$

where c_k is a constant. Capital adjustment costs have two components: $\bar{\Psi}_t^k$ denotes average adjustment costs and Ψ_t^z is a factor that scales average adjustment costs.

Capital adjustment costs are usually motivated by disruption costs caused by the installation or replacement of capital, delivery lags, and time to build. To capture these, I assume a standard quadratic form for average adjustment costs given by

$$\bar{\Psi}_t^k = c_k \left(\frac{i_t z_t^a}{k_t} \right)^2 \frac{k_t}{z_t^a}, \tag{1.9}$$

where c_k is a positive constant and $\frac{k_t}{z_t^a}$ is the replacement cost of capital at the average value of the firm-specific IST level.[30]

Another factor of capital adjustment costs is costly learning because of changes in the structure of production (Cooper and Haltiwanger (2006)). Such costs have two major dimensions. First, adoption can be costly to the extent that the technology gap is large between firm assets in place and new capital formed through investment. The second dimension depends on the characteristics of the workforce inside the firm, namely how open the employees are to the disruption characterized by the technology gap. To capture these two dimensions of technology adoption, I assume the following form for Ψ_t^z:

$$\Psi_t^z = c_z \left(\tilde{z}_t - 1 \right) \frac{l_t^y}{n_t}, \tag{1.10}$$

where c_z is a constant and I consider the case $c_z < 0$. Recall that $\mathbb{E}\left[\tilde{z}_t\right] = 1$. If a firm's investment opportunities embody a higher technology level than the average firm in the economy ($\tilde{z}_t > 1$), the firm has an opportunity to lower capital adjustment costs in addition to achieving higher efficiency of investment because of the role of z_t in (1.3). The adjustment cost savings are increasing in the fraction of young employees in the firm's workforce. However, if the firm is facing lower levels of embodied technology ($\tilde{z}_t < 1$), investment becomes costlier. The presence of a high fraction of old employees mitigates the additional costs of capital adjustment in this case.

The assumption of lower adjustment costs in the case of high embodied technology levels

[30]The z_t^a terms make capital adjustment costs grow at the same rate as other cash flow components. See Appendix D for details.

strengthens the effect of investment-specific technology on real investment opportunities.[31] Furthermore, this specification allows for an interaction between the efficiency of technology adoption characterized by adjustment costs and the composition of the workforce. As discussed above, high levels of $\tilde{z}_t$ can be interpreted as the presence of investment opportunities that embody a technology level that has not been experienced widely in the economy. The adjustment cost factor specified in (1.10) implies that firms with a younger workforce have an advantage in this case: they can adopt new technologies at a lower cost. This captures the idea that young college graduates are less entrenched in the status quo of existing firm operations and are more open to learning about and adapting to new technologies.[32] If the firm faces a lower level of embodied technology in new capital compared to the average firm in the economy, this technology level is likely to have been embodied in older vintages of capital as well. In other words, the technology gap between new capital and existing assets in place is not large. Older employees have more experience with such capital and therefore constitute a comparative advantage to the firm compared to younger employees.

1.3.2. Stochastic processes

The logarithm of aggregate disembodied technology (TFP) follows a random walk with drift:

$$\log\left(\frac{a_{t+1}}{a_t}\right) = \mu_a + \sigma_a \epsilon^a_{t+1}, \tag{1.11}$$

where μ_a is the drift, σ_a is the conditional volatility, and ϵ^a_{t+1} is a random shock that follows an *iid* standard normal distribution. The logarithm of firm-specific productivity follows an

[31] This specification is similar to models where (positive) investment-specific technology shocks are modeled as (negative) shocks to adjustment costs instead of specifying them in capital accumulation directly. See, e.g., Belo, Lin, and Bazdresch (2014).

[32] This is closely related to Acemoglu, Akcigit, and Celik (2014), who study the relation between manager age and firms' openness to innovation and technology adoption. They find firms that are more "open to disruption" tend to hire younger managers. The notion of employees and technology in this paper is more general (all skilled employees and all investments are considered rather than managers and firm innovation only), but high $\tilde{z}_t$ firms can be considered open to disruption, and such firms will optimally choose to hire younger employees because of the assumptions on the structure of adjustment costs. This is in line with the causal chain in the findings of Acemoglu, Akcigit, and Celik (2014) that young managers are not necessarily making firms more open to innovation, but such firms decide to hire young managers.

AR(1) process:

$$\log(u_{t+1}) = (1-\rho_u)\bar{u} + \rho_u \log(u_t) + \sigma_u \epsilon^u_{t+1}, \tag{1.12}$$

where ρ_u denotes persistence, $\bar{u}$ is the unconditional mean of log productivity, σ_u is the conditional volatility, and ϵ^u_{t+1} is a standard normal variable that is *iid* over time and across firms.

The logarithm of aggregate embodied technology (IST) follows a random walk with drift as well:

$$\log\left(\frac{z^a_{t+1}}{z^a_t}\right) = \mu_z + \sigma_z \epsilon^z_{t+1}, \tag{1.13}$$

where μ_z is the drift, σ_z is the conditional volatility, and ϵ^z_{t+1} a random shock that follows an *iid* standard normal distribution. The logarithm of firm-specific embodied technology follows an AR(1) process:

$$\log(\tilde{z}_{t+1}) = (1-\rho_z)\bar{z} + \rho_z \log(\tilde{z}_t) + \sigma_{\tilde{z}} \epsilon^{\tilde{z}}_{t+1}, \tag{1.14}$$

where ρ_z denotes persistence, $\bar{z}$ is the unconditional mean of the log IST level, $\sigma_{\tilde{z}}$ is the conditional volatility, and $\epsilon^{\tilde{z}}_{t+1}$ is a standard normal variable that is *iid* over time and across firms.

1.3.3. Wages and the stochastic discount factor

The present model provides a partial equilibrium description of a single firm. Therefore, I specify wages and the stochastic discount factor (SDF) exogenously, and assume that all firms in the economy face identical wage and SDF dynamics.

The model assumptions in Section 1.3.1 and 1.3.2 imply that the number of employees inside the firm grows over time. Following Belo, Lin, and Bazdresch (2014), I assume stationary wage rates such that the wage bill of the firm and output follow the same balanced growth path. The wage rate of young employees is given by

$$w_t^y = \bar{w}^y \exp(\tau_a^y \, \Delta \log(a_t) + \tau_z^y \, \Delta \log(z_t^a)), \tag{1.15}$$

where $\bar{w}^y$ controls the wage level, while τ_a^y and τ_z^y determine the sensitivity of wages to aggregate TFP and IST shocks, respectively. Analogously, the wage rate of old employees is given by

$$w_t^o = \bar{w}^o \exp(\tau_a^o \, \Delta \log(a_t) + \tau_z^o \, \Delta \log(z_t^a)). \tag{1.16}$$

In the quantitative assessment of the model, I calibrate the wage process based on empirical evidence as discussed in Section 1.3.5.

I specify a log-linear SDF in aggregate disembodied and embodied shocks:

$$M_{t,t+1} = \exp(-r_f) \, \frac{\exp(-\lambda_a \sigma_a \epsilon_{t+1}^a - \lambda_z \sigma_z \epsilon_{t+1}^z)}{\mathbb{E}_t \left[\exp(-\lambda_a \sigma_a \epsilon_{t+1}^a - \lambda_z \sigma_z \epsilon_{t+1}^z)\right]}, \tag{1.17}$$

where r_f is the constant risk-free rate, λ_a is the market price of TFP risk, and λ_z is the market price of IST risk.[33] While the SDF in the present model is specified exogenously, the literature offers some guidance on the economic content of market prices of risk. In general equilibrium models with a representative agent, the SDF represents marginal utility. The market price of disembodied shocks that drive the productivity of assets in place, λ_a, is unambiguously positive in traditional production-based asset pricing models (e.g., Jermann (1998)). Papanikolaou (2011) studies the pricing of aggregate embodied shocks in a two-sector general equilibrium model. Assuming recursive utility for the representative agent (Epstein and Zin (1989a), Duffie and Epstein (1992)), Papanikolaou shows that the sign of the market price of embodied technology risk depends on preferences. While the impact of embodied shocks on current consumption is negative, as they incentivize a substitution from consumption to investment, recursive utility agents' marginal utility also depends on shocks to the future consumption path. Positive embodied shocks improve future consumption

[33] The partial equilibrium models of Kogan and Papanikolaou (2014) and Belo, Lin, and Bazdresch (2014) also use this form for the SDF.

growth because of more intensive and more efficient capital formation. Therefore, the market price of risk for disembodied shocks depends on how the representative agent's marginal utility is affected by shocks that improve the future growth prospects of the economy. A positive shock to the future consumption path lowers marginal utility in case the recursive utility agent prefers the early resolution of uncertainty, while it increases marginal utility otherwise. I discuss the quantitative implications of the market prices of risk for the present model in Section 1.3.5.

1.3.4. Firm problem

Each firm in the economy solves a standard equity value maximization problem assuming no financial leverage. The total costs of investment and hiring are given by

$$\Psi_t^T = i_t + \Psi_t^k + \Psi_t^n. \tag{1.18}$$

The firm pays dividend d_t, which is what remains from output after paying wages, investment expenditures, and adjustment costs, is given by

$$d_t = y_t - w_t^y \, l_t^y - w_t^o \, l_t^o - \Psi_t^T. \tag{1.19}$$

The cum-dividend value of the firm at time t is then given by

$$p_t = \max \mathbb{E}_t \left(\sum_{\tau=0}^{\infty} M_{t,t+\tau} \, d_{t+\tau} \right), \tag{1.20}$$

where the maximization problem is solved over $\{i_{t+\tau}, k_{t+\tau+1}, h_{t+\tau}^y, l_{t+\tau+1}^y, h_{t+\tau}^o, l_{t+\tau+1}^o\}_{\tau=0}^{\infty}$ subject to the law of motion for capital, both types of labor, and the stochastic processes. The set of state variables for the firm problem is given by $\Phi_t = \{u_t, a_t, \tilde{z}_t, z_t^a, k_t, l_t^y, l_t^o\}$. Finally, the gross equity return can be written as

$$R_{t+1} = \frac{p_{t+1}}{p_t - d_t}. \tag{1.21}$$

In the next section, I calibrate the model to inspect the mechanism behind the demographic dimension of hiring policy and expected returns.

1.3.5. Calibration

I calibrate the model at the monthly frequency and aggregate the results to annual frequency whenever the empirical counterpart of a moment is available at the annual frequency. I simulate 500 panels with 2,500 firms and a length of 50 years. Table 1.16 reports the parameter values and Table 1.17 reports the main average results from the model simulations. Data values correspond to the period from 1965 to 2015 unless otherwise stated. I set the shares of capital and labor, α_k and α_n, such that they imply a returns-to-scale parameter of 0.85 with shares of 0.35 and 0.65, respectively. I set the depreciation rate of capital to 0.01 to be in line with the depreciation rate of equipment in the data. The separation rate of employees is 0.03 to replicate the average aggregate labor separation rate in the data. I set the growth rate of TFP and IST shocks to the average growth of aggregate output in the data. There are wide-ranging estimates for the conditional volatility of aggregate IST shocks in the literature (see, e.g., Justiniano, Primiceri, and Tambalotti (2011), Schmitt-Grohé and Uribe (2011)). I set the annualized value to 0.08, which is within the estimated values in the literature, along with a conditional volatility of 0.035 for the aggregate TFP shock, which results in a volatility of 13% for aggregate dividend growth. Firm-specific productivity shocks are the source of heterogeneity in the present model. The unconditional average value ($\bar{z}$) of firm-specific IST is chosen such that $\tilde{z}_t$ has an average of 1. The average of (log) firm-specific productivity ($\bar{u}$) is a scaling variable, which I set to -3.4. The volatility and persistence parameters of firm-specific productivity shocks are calibrated jointly with adjustment cost parameters to generate realistic implications for the cross-section and time series of investment and hiring rates.

Parameters governing wage dynamics are chosen to replicate their data counterparts. The young-to-old ratio in average wages in the data is 0.61. I set the efficiency units of young and old employees, e_y and e_o, to replicate this number by setting the scale parameters for wages, $\bar{w}^y$ and $\bar{w}^o$, proportional to the efficiency units. I analyze the sensitivities of wages to aggregate shocks in the data using the KLEMS dataset. Table 1.20 shows the loadings of average young and old wages per skilled employee to the TFP measure of Fernald (2014) and the IST measure of Israelsen (2010). These two shocks have high explanatory power for one-, five-, and seven-year wage dynamics. Furthermore, young wages have a lower loading on the TFP shock and react more to the IST shock compared to the average wages of the old. Although wages are exogenously specified here, this is in line with the motivation of this model. As they play an important role in times of favorable shocks to technology embodied in new capital, young employees' compensation reacts more to the IST shock. Old employees have a more important role in existing operations, which is in line with wages that comove more with the productivity of assets in place. I target the annual average dynamics of wages in the calibration.[34] I set the scaling parameters for wages targeting the labor share in the data.[35] The labor share tends to be higher for value (high B/M) firms, which is a feature replicated by the model.

The adjustment cost parameters along with productivity processes are important for the moments related to investment and hiring. The model generates substantial time-series and cross-sectional volatility in hiring and investment rates but still undershoots these quantities in the data. This is due to the smooth form of adjustment cost functions, which lead to a lack of lumpiness in hiring and investment. I conjecture that one could improve on this dimension by adding a fixed component to the adjustment costs[36], but I keep the simpler adjustment cost specification and focus on the features of the model that help explain the novel evidence in Section 1.2. The parameter that determines the gains from having more young employees in the firm in the case of higher IST levels is c_z. It determines the average level and dynamics of the young-to-old ratio inside the firm. I set c_z to match the young-to-

[34] The model assumes identical wages for all young and old employees in the economy. See Appendix A1.3 for a discussion of empirical cross-sectional variation in wages.

[35] I target the total wage bill in the calibration of the labor share including unskilled labor. Section 1.3.7 discusses how unskilled labor can be included in the present model.

[36] See Belo, Lin, and Bazdresch (2014) for an extensive analysis of fixed and variable adjustment costs in capital and labor.

old ratio in the economy as well as ω for the high and low ω portfolios, which are the model counterparts of portfolios Y and O in the empirical analysis of Section 1.2. Note that, in the case of $c_z = 0$, firms find it optimal to hire old employees only, as there is no comparative advantage for the young and the old provide more efficiency units in production while their quantity is not costlier to adjust.

1.3.6. Mechanism and asset pricing

Firms have differential exposure to aggregate TFP and IST shocks at every point in time depending on the history of firm-specific shocks that determines their current capital and labor quantities as well as the composition of their workforce. Because both shocks affect the SDF in (2.15), an approximate expression for the conditional risk premium of a firm can be written as

$$\mathbb{E}_t[r^i_{t+1} - r_f] \approx \beta^i_{a,t}\, \lambda_a\, \sigma_a + \beta^i_{z,t}\, \lambda_z\, \sigma_z, \tag{1.22}$$

where $\beta^i_{a,t}$ and $\beta^i_{z,t}$ are conditional exposures of firm i to TFP and IST shocks, respectively.

The central object of this paper is the adjustment of the workforce composition, namely when firms decide to increase or decrease the fraction of young employees represented by the variable ω. The benefits from having young employees, when the firm faces high embodied technology in new capital, is represented by high $\tilde{z}$. Therefore, the transition from low to high $\tilde{z}$ states correspond to periods of high ω as depicted in Figure 1.8, which shows the impulse response of quantities to a positive $\tilde{z}$ shock. Upon a positive shock to $\tilde{z}$, the firm increases the share of young employees rapidly. A transition to higher $\tilde{z}$ values also incentivizes investment because capital goods are effectively cheaper in this case. However, investment is initially low and spikes about one year after the positive shock to $\tilde{z}$, namely once the firm approaches the desired share of young employees in the workforce. At the time of the investment spike, ω is still positive; hence, there is still room for a higher share of young employees inside the firm. After two years, investment starts to drop once the $\tilde{z}$ shock is mean-reverting, and ω goes even below zero because the firm approaches the new higher level of capital and has more assets in place. Experienced workers are more productive in working with assets in place.[37]

A high value for $\tilde{z}$ lowers the replacement cost of capital (k/z) and increases the share of growth opportunities in the firm value. The exposure of growth opportunities to aggregate IST shocks is particularly high in times of high investment, and this exposure is amplified by adjustment costs that have not yet lowered fully through the adjustment of the labor composition. The YMO portfolio return in the model, which is long in high ω firms and short in low ω firms, has a high exposure to aggregate IST shocks. Therefore, a positive value for the market price of aggregate IST shocks (λ_z) helps explain the high average returns to the YMO strategy.

The primary focus of models explaining the cross-section of expected stock returns, is the value premium. The market-to-book ratio, which is the defining variable of the value premium, can be defined as $\frac{p}{k/z}$ in the model where k/z is the replacement cost of capital. A positive shock to $\tilde{z}$ lowers the replacement cost of capital, shifting the firm toward being categorized as a growth firm. Growth opportunities become a higher share of firm value, making growth firms more exposed to aggregate IST shocks.

A recent strand of literature explains the value premium using this differential impact of IST shocks on value and growth firms, and attaching a negative market price of risk to IST shocks. As discussed in Section 1.3.3, Papanikolaou (2011) achieves this in general equilibrium assuming a preference for the late resolution of uncertainty for the representative agent.[38] Kogan and Papanikolaou (2013) and Kogan and Papanikolaou (2014) study partial equilibrium models like the one described in the current paper and assume a negative price

[37]See Appendix A1.2 for a discussion of the forward-looking nature of ω, and the backward looking information in the share yof young employees in the workforce. Table 1.19 shows that the model replicates this feature of the data.

[38]Other general equilibrium mechanisms with a similar pricing argument are Gârleanu, Kogan, and Panageas (2012), who argue that growth stocks hedge existing agents against future negative shocks to their human capital caused by innovation that benefits younger generations, and Kogan, Papanikolaou, and Stoffman (2016), who construct a model with incomplete markets and an unequal distribution of rents from innovation. Although not modeled as IST shocks, other papers argue that innovation lowers the marginal utility of the representative agent because of its long-run benefits, e.g., Kung and Schmid (2015).

of risk for IST shocks explicitly.[39] These papers also provide evidence that growth firms are indeed more exposed to proxies of IST shocks, as also shown in Section 1.2.5.1. In recent empirical work, Garlappi and Song (2016) argue that measurements of exposures to IST shocks are highly dependent on the sample period used and the choice of test assets.

Another way of achieving the value premium within the neoclassical model of the firm is operating leverage. Zhang (2005) shows that capital adjustment costs give rise to the value premium and can be amplified by costly reversibility as in Abel and Eberly (1996), namely that downward adjustment of capital is costlier than expanding capital. In more recent work, Favilukis and Lin (2014) show the impact of wage rigidity on the aggregate market and the value premium. These models feature mechanisms that make the costs of the firm less procyclical than revenue, which amplifies the procyclicality of cash flows, increasing value firms' exposure to aggregate TFP shocks.[40]

The discussion above suggests that high positive values for λ_a help replicate the value premium, while there is a tension in the explanation of young-to-old spread and the value premium based on λ_z. While a positive value for λ_z can replicate the YMO spread, the exposure to embodies shocks helps explain the value premium with negative values of λ_z. A positive average YMO spread along with a positive value premium can be achieved by the choice of a positive λ_z, and a positive and high λ_a such that the impact of TFP shocks dominates the value premium. I confirm this by choosing values for λ_a and λ_z to match the average market excess return, stock market volatility, the average YMO spread, and the value premium.[41] The positive YMO spread is almost entirely compensation for the risk associated with IST shocks. The market price of TFP shocks is large enough to generate

[39] Belo, Lin, and Bazdresch (2014) also uses this approach in seeking an explanation for the gross hiring spread, namely that firms with low hiring rates have higher expected returns in the cross-section.

[40] Specifically, adjustment costs prevent the firm from adjusting capital rapidly upon productivity shocks. Costly reversibility burdens the firm with unproductive capital in times of low productivity, as disinvestment is particularly costly. Finally, wage rigidity leads to labor costs that do not decrease proportional to productivity, making firm cash flows riskier.

[41] Specifically, I minimize a weighted sum of squared deviations of model values from data for these four moments, and search over integer values for λ_a and λ_z. All return moments have unit weight, while the weight of stock market volatility is one half.

a value premium that is not overturned by the low exposure of value firms to IST shocks. The opposite exposures of the YMO and HML spreads to aggregate shocks gives rise to a negative correlation between the two, just as in the data. Finally, the model also generates a return spread between low and high hiring firms. The hiring return spread has a correlation of 89% with value minus growth in the model compared to 53% in the data.

Two mechanisms for operating leverage are embedded in the present model. Column 2 of Table 1.18 reports results from a calibration where the wage level parameters $\bar{w}^y$ and $\bar{w}^o$ are set to half of the values in the baseline calibration. In this case, the wage share of output is low substantially lowering the operating leverage effect from wage costs. This causes a substantial drop in the value premium. Column (4) of Table 1.18 reports results from the model with $c_z = 0$, which shuts down the dependence of capital adjustment costs on the composition of the workforce. Firms exclusively employ old employees in this case, because an old employee has higher efficiency units in production while having the same adjustment cost. Therefore, it is more effective to use only old employees leading to a corner solution that the firm employs no young employees. The dependence of capital adjustment costs on workforce composition also induces an asymmetry in capital adjustment costs. Times of high investment tend to be times of lower than average adjustment costs (because $c_z < 0$) while low investment is usually associated with high adjustment costs. The average value of Φ_t^z is - 0.41 in periods of positive investment while it is 0.24 in times of disinvestment. As seen in Table 1.18, in the case of $c_z = 0$ the value premium drops substantially in this case as well. Value firms tend to have low firm-specific productivity, u. Therefore, they try to fire workers and disinvest, yet costly adjustment prevents them from making rapid adjustments at the extensive margin. At the same time, low values for $\tilde{z}$ imply a high replacement cost of capital, which is also a feature of value firms. Hence, value firms are expected to have positive exposure to aggregate TFP shocks and negative exposure to IST shocks. Table 1.17 shows that the exposure of returns to aggregate shocks is in line with the empirical evidence discussed in Section 1.2.5.1.

Finally, the momentum effect in the model arises due to the positive exposure of winners to IST shocks as shown in Table 1.17. Upon the arrival of a positive firm-specific IST shock, the firm starts adjusting the workforce toward young employees and the investment spike exhibits a slow and persistent pattern implying returns that are highly exposed to aggregate IST shocks.

1.3.7. Extensions

The calibration of the baseline model in Section 1.3.5 splits the workforce into demographic groups only, but does not consider the role of skilled and unskilled labor separately. However, part of the wage bill of firms is naturally paid to unskilled workers, they are thus represented in the labor share. In recent work, Belo, Lin, Li, and Zhao (2016) show that the hiring return spread documented in Belo, Lin, and Bazdresch (2014) is largely driven by industries that have a high share of skilled labor in the workforce. They argue that the hiring process for skilled employees is costlier, resulting in a larger association of hiring with asset prices through the adjustment cost channel. Appendix A1.6 illustrates an extension of the baseline model featuring unskilled labor in production. I assume that unskilled labor can be chosen every period and the hiring process does not involve adjustment costs unlike skilled labor consistent with the evidence in Belo, Lin, Li, and Zhao (2016). This approach does not increase the computational burden of the model because the number of endogenous state variables stays the same as in the baseline model. I calibrate this version of the model, as discussed in Appendix A1.6, by targeting the total labor share of output. The asset pricing implications are largely unaffected. The value premium and the gross hiring spread are slightly lower due to the lower quantity of labor adjustment costs, and the time-series and cross-sectional volatilities of the hiring rate are lower in this version of the model. However, the young-minus-old hiring spread of the skilled workforce is still large which is the main objective of this paper.

The baseline model assumes that a young employee is less productive with all assets in place compared to an old employee. While this captures the value of experience in production, it may be counterfactual in the special case that most of assets in place have been installed recently. One can think of the possibility that a firm that has a high share of recently installed capital may want to hire younger employees because they may be more proficient in production with young capital. Lin, Palazzo, and Yang (2016) group firms by the average age of physical capital and find that the capital of the lowest decile portfolio has an average age of 9.5 quarters while it reaches 39 quarters for the highest decile. Hence, there is not a large number of firms with a high share of very recently installed capital, say, within the last year. Another dimension that the baseline model does not feature is that employees may become experienced inside the firm. In the current setup, however, the channel to increase the quantity of old labor is hiring from outside of the firm. To address these concerns, I consider a constant transition rate from the young to the old workforce of the firm by modifying the laws of motion for number of employees as follows:

$$l_{t+1}^{y} = (1 - s)\, l_t^{y} - s_y l_t^{y} + h_t^{y}, \tag{1.23}$$

and

$$l_{t+1}^{o} = (1 - s)\, l_t^{o} + s_y l_t^{y} + h_t^{o}, \tag{1.24}$$

where s_y is the fraction of young employees that joins the old workforce while staying inside the firm. In this case, a young employee does not necessarily remain less productive with existing capital. By the time the installation of capital due to a favorable firm-specific IST shock is complete, there is a probability that the employee switches to the old workforce and contributes to production with a high level of efficiency units. Table 1.22 reports results by setting $s_y = 0.05$ and shows that this additional feature has no significant effect on main results.

Finally, the empirical evidence in Section 1.2 is at the industry level while the model is simulated at the firm level. As $\tilde{z}_t$ represents the technology embodied in new capital, and firms in the same industry are likely to use similar capital goods, one can group firms into industries where firms in the same industry have perfectly correlated $\tilde{z}_t$ processes. When the model is simulated with 25 industries containing 100 industries each, results are very close to the baseline specification. I do not report results from this simulation for brevity.

1.4. Conclusion

This paper shows that the demographic dimension of hiring activity is informative about the risks and opportunities that firms face, providing an ideal venue to study the interaction between demographics of the workforce and asset prices in an investment-based framework. Specifically, I document that a focus on young and skilled implies higher expected equity returns and is a leading indicator of medium-term period characterized by higher embodied technology in new capital for U.S. industries. Industries that shift their skilled workforce toward younger employees are more exposed to fluctuations in technological progress embodied in new capital which points to similar behavior to growth firms, while they have higher expected returns in contrast to growth firms. I provide a partial-equilibrium of the firm where demographic groups play differential roles in production and capital adjustment. The model offers an explanation for the implications of hiring demographics for equity returns, as well as for the interaction of this novel dimension of the data with established patterns in the cross-section of firms.

Table 1.1: Industries

1	Mining and quarrying
2	Food products, beverages, and tobacco
3	Textiles, textile products, leather, and footwear
4	Wood and products of wood and cork
5	Pulp, paper, paper products, printing and publishing
6	Coke, refined petroleum products, and nuclear fuel
7	Chemicals and chemical products
8	Rubber and plastics products
9	Other non-metallic mineral products
10	Basic metals and fabricated metal products
11	Machinery
12	Electrical and optical equipment
13	Transport equipment
14	Other manufacturing
15	Electricity gas and water supply
16	Construction
17	Wholesale trade
18	Sale and maintenance of motor vehicles, retail sale of fuel
19	Retail trade
20	Accomodation and food services
21	Transport and storage
22	Post and telecommunications
23	Business services
24	Healthcare
25	Personal services
26	Financial activities
27	Real estate activities

Notes: Table lists the industries in the KLEMS data set that are used in this paper.

Table 1.2: Portfolio Characteristics

	Y	M	O
ω	0.05	0.00	-0.06
$\log(l_t^y/l_{t-1}^y)$	0.08	0.05	0.01
$\log(l_t^o/l_{t-1}^o)$	0.03	0.05	0.06
l_t^y/l_t^o	0.18	0.16	0.16
l_{t-1}^y/l_{t-1}^o	0.17	0.16	0.17
Market share	0.18	0.65	0.17
Book-to-market ratio			
Mean	0.65	0.61	0.72
Median	0.67	0.68	0.71
Employment growth			
Mean	0.05	0.04	0.04
Median	0.03	0.03	0.02
Investment rate			
Mean	0.19	0.18	0.17
Median	0.21	0.22	0.19
Profitability			
Mean	0.09	0.07	0.08
Median	0.08	0.07	0.07

Notes: Columns Y, M, and O refer to the young, medium, and old hiring portfolios, respectively. All statistics are computed in the cross-section of stocks every year from 1966 to 2015. Time-series averages are reported. ω is the log change in the ratio of young employees to old employees. Market share is the average market capitalization of stocks in the respective portfolio divided by the total market capitalization.

Table 1.3: Portfolio Returns

	Y	M	O	YMO
		Panel A: Excess returns		
$r - r_f$	9.17	5.08	4.52	4.64
	[3.73]	[2.21]	[1.79]	[3.09]
SR	0.52	0.32	0.26	0.40
		Panel B: CAPM		
α	3.44	-0.70	-0.74	4.18
	[2.73]	[-1.51]	[-0.49]	[2.78]
MKT	1.00	1.01	0.90	0.10
	[31.44]	[107.52]	[26.16]	[2.19]
R^2	0.81	0.97	0.75	0.02
		Panel C: Fama-French		
α	3.26	-0.45	-2.30	5.56
	[2.66]	[-1.01]	[-1.86]	[3.64]
MKT	0.99	1.00	0.95	0.04
	[34.46]	[121.52]	[28.91]	[0.71]
SMB	0.06	0.01	0.05	0.02
	[1.57]	[0.61]	[0.93]	[0.24]
HML	-0.12	-0.05	0.31	-0.30
	[-2.02]	[-2.57]	[4.60]	[-3.64]
R^2	0.81	0.97	0.78	0.08

Notes: Columns Y, M, and O refer to the young, medium, and old hiring portfolios, respectively. YMO is the difference between the returns of young and old hiring portfolios. Panel A reports portfolio excess returns and annualized Sharpe ratios (SR). Panel B reports results from CAPM time-series regressions. Panel C reports results from time-series regressions using the Fama and French (1993) 3-factor model. α is the regression intercept. Lines MKT, SMB, and HML report the coefficients on the corresponding factors. Data are monthly from January 1966 to December 2015. Returns and α's are multiplied by 1,200. t-statistics in brackets are based on Newey-West standard errors.

Table 1.4: Alternative Factor Models

	Y	M	O	YMO
Panel A: q factors				
α	3.58	-0.08	-2.14	5.72
	[2.73]	[-0.12]	[-1.35]	[2.78]
MKT	1.01	1.00	0.94	0.07
	[32.94]	[93.86]	[28.71]	[1.33]
SMB	0.07	-0.01	0.05	0.02
	[1.53]	[-0.68]	[0.72]	[0.21]
INV	-0.08	-0.09	0.33	-0.29
	[-1.37]	[-1.63]	[2.55]	[-1.98]
PROF	0.09	-0.01	0.00	0.09
	[1.45]	[-0.44]	[0.03]	[0.78]
R^2	0.82	0.98	0.78	0.05
Panel B: Fama-French 5 factors				
α	3.04	-0.28	-3.12	6.16
	[2.37]	[-0.56]	[-2.21]	[3.64]
MKT	1.00	0.99	0.97	0.03
	[35.82]	[117.52]	[30.19]	[0.51]
SMB	0.07	0.01	0.08	-0.01
	[1.36]	[0.61]	[1.58]	[-0.12]
HML	-0.09	-0.03	0.26	-0.28
	[-1.54]	[-1.43]	[3.56]	[-2.48]
INV	0.05	-0.05	0.10	-0.05
	[0.49]	[-1.64]	[1.11]	[-0.37]
PROF	0.02	-0.01	0.14	-0.12
	[0.21]	[-0.35]	[1.91]	[-1.10]
R^2	0.81	0.97	0.79	0.08

Notes: Columns Y, M, and O refer to the young, medium, and old hiring portfolios, respectively. YMO is the difference between the returns of young and old hiring portfolios. Panel A reports results from time-series regressions using the Hou, Xue, and Zhang (2014) 4-factor model. Panel B reports results from time-series regressions using the Fama and French (2015) 5-factor model. Lines MKT, SMB, HML, INV, and PROF report the coefficients on the corresponding factors. Data are monthly from January 1966 to December 2015. Returns and α's are multiplied by 1,200. t-statistics in brackets are based on Newey-West standard errors.

Table 1.5: Firm-Level Stock Return Predictability

	(1)	(2)	(3)	(4)	(5)	(6)
ω	0.14	0.15	0.15	0.16	0.14	0.16
	[4.11]	[4.24]	[4.20]	[4.43]	[4.13]	[4.64]
I/K		-0.14				-0.12
		[-5.22]				[-4.48]
H/N			-0.09			-0.08
			[-4.15]			[-3.38]
B/M				0.03		0.02
				[5.13]		[4.50]
M					-0.17	-0.13
					[-3.17]	[-3.02]
$\bar{R}^2$	0.15	0.16	0.15	0.15	0.14	0.17

Notes: Table reports results from pooled OLS regressions of annual stock returns on five different combinations of characteristics ω (difference between young and old hiring rate), I/K (investment rate), H/N (gross hiring rate), B/M (book-to-market ratio), M (log market cap). The independent variables are winsorized at the top and bottom 0.5 percentile resulting in 116,287 firm-year observations. Estimates of intercepts are not reported. Regressions include year and industry fixed effects. t-statistics are computed from standard errors clustered at the firm level.

Table 1.6: Double-Sorted Excess Portfolio Returns

	High	Med	Low	High - Low	α_{hl}	High	Med	Low	High - Low	α_{hl}
	Panel A: Book-to-market ratio					Panel B: Size				
Y	11.33	8.95	7.78	3.54	-0.51	8.95	12.08	10.64	-1.69	1.09
				[1.67]	[-0.32]				[-0.51]	[0.53]
M	8.80	5.99	4.84	3.96	-0.14	5.10	7.05	8.94	-3.48	-0.74
				[2.34]	[-0.14]				[-1.34]	[-0.47]
O	8.76	5.66	3.13	5.63	2.97	4.37	7.58	9.57	-5.19	-3.04
				[2.63]	[1.56]				[-1.92]	[-1.26]
YMO	2.57	3.28	4.66			4.58	4.55	1.07		
	[1.55]	[2.07]	[2.89]			[3.39]	[2.56]	[0.43]		
α_{ymo}	2.35	3.90	5.84			5.37	5.62	1.22		
	[1.15]	[2.18]	[3.44]			[3.61]	[2.44]	[0.42]		
	Panel C: Investment rate					Panel D: Employment growth				
Y	6.11	8.84	10.56	-4.45	-2.22	7.15	9.34	11.17	-4.02	-1.66
				[-1.58]	[-0.93]				[-2.10]	[-0.87]
M	4.09	5.79	6.97	-2.88	-0.87	4.33	5.14	7.71	-3.37	-1.51
				[-1.27]	[-0.57]				[-2.23]	[-1.36]
O	2.80	4.12	6.55	-3.75	-2.51	4.63	4.85	5.63	-1.00	0.08
				[-1.51]	[-1.24]				[-0.62]	[0.05]
YMO	3.31	4.72	4.01			2.52	4.48	5.54		
	[1.54]	[2.88]	[2.23]			[1.48]	[3.18]	[3.20]		
α_{ymo}	4.62	5.84	4.33			4.29	4.90	6.03		
	[1.75]	[3.40]	[2.16]			[2.23]	[3.27]	[3.03]		

Notes: Table reports excess returns from two-way double sorts. Rows Y, M, and O refer to the young, medium, and old hiring portfolios, respectively. YMO is the difference between the returns of young and old hiring portfolios. The computation of sorting variables from accounting data used to form portfolios High, Med, and Low, is described in Appendix A1.1. Breakpoints for the accounting variable are 30^{th} and 70^{th} percentiles. α_{hl} is the FF-3 model alpha of the corresponding High - Low return. α_{ymo} is the FF-3 model alpha of the corresponding YMO return. Data are monthly from January 1966 to December 2015. Returns are value-weighted and multiplied by 1,200. t-statistics in brackets are based on Newey-West standard errors.

Table 1.7: Industries by Exposure to YMO

1	Computer software
2	Electronic equipment
3	Computers
4	Measuring & cont. equipment
5	Steel works
45	Defense
46	Plastic products
47	Personal services
48	Entertainment
49	Soda

Notes: Table lists five industries that have the highest and lowest coefficient on YMO in monthly time-series regressions of portfolio excess returns on YMO. 49 industry return series from Kenneth French's website are used. Data are monthly from January 1966 to December 2015.

Table 1.8: Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: YMO				
	5.41	4.44	3.96	3.48	3.71	4.08	3.96	4.24
	[2.30]	[2.39]	[2.60]	[2.08]	[1.96]	[2.20]	[2.33]	[2.68]
				Panel B: Fama-French 5 factor				
α	8.28	5.88	5.64	4.06	7.92	6.96	3.84	5.84
	[3.01]	[3.26]	[3.66]	[2.02]	[3.74]	[3.48]	[2.15]	[3.02]
MKT	0.04	-0.02	0.01	0.07	-0.11	-0.06	0.14	0.02
	[0.60]	[-0.29]	[0.23]	[1.31]	[-2.00]	[-1.29]	[2.69]	[0.42]
SMB	-0.11	0.06	0.01	0.03	-0.04	0.15	0.12	0.00
	[-1.02]	[0.66]	[0.11]	[0.46]	[-0.71]	[2.68]	[1.45]	[0.01]
HML	-0.42	-0.20	-0.36	-0.27	-0.33	-0.26	-0.28	-0.27
	[-2.47]	[-1.61]	[-3.59]	[-2.63]	[-2.81]	[-2.46]	[-2.45]	[-2.34]
INV	0.05	-0.11	0.00	0.05	-0.46	-0.41	0.03	-0.05
	[0.23]	[-0.72]	[0.02]	[0.37]	[-2.24]	[-0.66]	[0.31]	[-0.45]
PROF	-0.23	-0.14	-0.10	-0.06	-0.40	-0.11	0.02	-0.10
	[-0.99]	[-1.17]	[-1.04]	[-0.58]	[-2.68]	[-0.66]	[0.10]	[-0.87]

Notes: Panel A reports YMO, the difference between the returns of young and old hiring portfolios, for seven alternative empirical settings:

(1) uses data from January 1966 to December 1989,
(2) uses data from January 1990 to December 2015,
(3) reports the result excluding financial and real estate industries,
(4) reports the result excluding all firms reporting positive R&D expenditures in Compustat,
(5) reports results with an age threshold of 35 between young and old,
(6) reports results with equal-weighting,
(7) reports results using a time-varying definition of skill.
(8) reports results using industry-specific age-cutoffs using the age at the 20th percentile of an industry in the previous year.
Panel B reports results from time-series regressions of YMO using the Fama and French (2015) 5-factor model. t-statistics in brackets are based on Newey-West standard errors.

Table 1.9: Five Portfolio Returns

	Y	2	3	4	O	YMO
			Panel A: Excess returns			
$r - r_f$	9.17	5.90	5.77	5.03	4.52	4.64
	[3.73]	[2.04]	[2.32]	[1.95]	[1.79]	[3.09]
			Panel B: CAPM			
α	3.44	-0.20	-0.19	-0.36	-0.74	4.18
	[2.73]	[-0.15]	[-0.23]	[-0.31]	[-0.49]	[2.78]
MKT	1.00	1.07	1.04	0.94	0.90	0.10
	[31.44]	[34.68]	[39.91]	[27.09]	[26.16]	[2.19]
R^2	0.81	0.84	0.90	0.78	0.75	0.02
			Panel C: Fama-French			
α	3.26	0.34	-0.30	-0.14	-2.30	5.56
	[2.66]	[0.34]	[-0.37]	[-0.13]	[-1.86]	[3.64]
MKT	0.99	1.02	1.02	0.90	0.95	0.04
	[34.46]	[51.82]	[53.00]	[29.92]	[28.91]	[0.71]
SMB	0.06	0.10	0.01	0.12	0.05	0.02
	[1.57]	[2.87]	[0.38]	[2.52]	[0.93]	[0.24]
HML	-0.12	-0.15	-0.10	-0.09	0.31	-0.30
	[-2.02]	[-3.46]	[-1.96]	[-1.47]	[4.60]	[-3.64]
R^2	0.81	0.86	0.90	0.79	0.78	0.08

Notes: Columns Y, 2, 3, 4 and O refer to the portfolios with the highest to lowest value of ω. YMO is the difference between the returns of young and old hiring portfolios. Panel A reports portfolio excess returns. Panel B reports results from CAPM time-series regressions. Panel C reports results from time-series regressions using the Fama and French (1993) 3-factor model. Data are monthly from January 1965 to December 2015. Returns and α's are multiplied by 1,200. t-statistics in brackets are based on Newey-West standard errors.

Table 1.10: Annual Portfolio Returns

	Y	M	O	YMO
		Panel A: Excess returns		
$r - r_f$	10.13	6.25	5.28	4.84
	[4.99]	[2.92]	[3.06]	[3.68]
		Panel B: CAPM		
α	3.78	-0.25	-0.32	4.10
	[2.38]	[-0.39]	[-0.24]	[3.02]
MKT	1.01	1.03	0.89	0.12
	[12.05]	[30.58]	[9.59]	[0.83]
R^2	0.75	0.95	0.76	0.02
		Panel C: Fama-French		
α	3.96	0.44	-2.58	6.53
	[2.44]	[0.71]	[-2.44]	[3.46]
MKT	0.99	0.99	0.95	0.03
	[11.83]	[37.16]	[18.38]	[0.30]
SMB	0.06	0.06	0.07	-0.01
	[0.58]	[2.06]	[1.03]	[-0.09]
HML	-0.05	-0.14	0.36	-0.42
	[-0.50]	[-2.79]	[4.48]	[-2.61]
R^2	0.75	0.96	0.84	0.12

Notes: Columns Y, M, and O refer to the young, medium, and old hiring portfolios, respectively. YMO is the difference between the returns of young and old hiring portfolios. Panel A reports portfolio excess returns. Panel B reports results from time-series regressions implied by the CAPM. Panel C reports results from time-series regressions using the Fama and French (1993) 3-factor model. Data are annual from 1966 to 2015. Returns and α's are multiplied by 1,200. t-statistics in brackets are based on Newey-West standard errors.

Table 1.11: Industry Momentum

Period	Sort	Low	2	3	4	High	High-Low	α_{capm}	α_{ff}	α_{mktymo}	α_{ymo}
Panel A: Fama-French 30 Industries											
1966-2015	6m-12m	4.05	5.71	6.53	7.92	8.53	4.48	3.43	5.13	2.28	2.78
							[2.87]	[2.40]	[3.51]	[1.36]	[1.85]
1966-1999	6m-12m	3.95	5.23	6.16	8.04	8.87	4.92	3.94	4.76	2.03	2.65
							[2.70]	[2.82]	[2.56]	[1.11]	[2.20]
1966-2015	2m-6m	4.90	6.95	7.43	6.66	7.11	2.21	3.23	5.62	3.10	2.19
							[1.68]	[1.99]	[2.56]	[2.12]	[1.73]
1966-1999	2m-6m	4.33	6.92	7.75	5.74	7.82	3.49	4.63	6.55	3.88	2.73
							[2.36]	[2.14]	[2.25]	[1.85]	[1.54]
Panel B: ISIC 27 Industries											
1966-2015	6m-12m	5.78	5.80	6.86	8.75	9.02	3.24	1.91	3.97	0.65	1.60
							[2.05]	[0.93]	[1.94]	[0.30]	[0.88]
1966-1999	6m-12m	4.59	4.97	6.31	9.47	10.20	5.60	3.98	4.91	2.02	3.22
							[2.36]	[1.59]	[1.64]	[0.82]	[1.42]
1966-2015	2m-6m	6.41	6.39	7.57	6.99	8.43	2.02	3.09	7.42	1.05	-0.18
							[0.96]	[1.83]	[2.20]	[0.50]	[-0.08]
1966-1999	2m-6m	6.33	5.45	7.38	6.49	9.44	3.10	4.08	8.63	1.06	-0.25
							[0.97]	[1.46]	[2.00]	[0.32]	[-0.08]

Notes: Table reports results for industry momentum. The "Period" column reports the sample period used. "Sort" is the period used to compute industry momentum: 6m-12m uses returns from 12-month to 6-month before portfolio formation. 2m-6m uses returns from 6-month to 2-month before portfolio formation as the sorting variable. The columns Low to High report excess returns of momentum portfolios from lowest to highest value for the corresponding momentum variable. High-Low is the average return from the strategy long in the highest and short in the lowest momentum portfolio. α_{capm} and α_{ff} are the intercepts from time-series regressions of the High-Low return based on CAPM and Fama and French (1993), respectively. α_{mktymo} is the intercept from the regression of the High-Low return on the market excess return and YMO. α_{ymo} is the intercept from the regression of the High-Low return on YMO. Data are annual and t-statistics in brackets are based on Newey-West standard errors.

Table 1.12: Macroeconomic Shocks

	YMO			HML			INDMOM		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Δa	-3.21	-3.45		3.97	4.84		-4.79	-5.84	
	[-1.46]	[-2.03]		[1.99]	[2.80]		[-2.01]	[-2.52]	
Δz	3.99			-1.18			2.66		
	[2.15]			[-0.65]			[1.92]		
R_m			-0.02			-1.28			0.97
			[-0.01]			[-0.86]			[0.57]
R_{imc}		1.65	1.57		-2.06	-1.87		1.67	1.49
		[4.20]	[3.59]		[-8.83]	[-6.60]		[11.75]	[8.44]
$\bar{R}^2$	0.07	0.27	0.19	0.03	0.46	0.37	0.08	0.39	0.24

Notes: Table reports results from OLS time series regressions of YMO, HML, and INDMOM returns on combinations of macroeconomic shocks. Δa is the growth of total factor productivity (TFP) from Fernald (2014). Δz is the growth of investment-specific technology (IST) from Israelsen (2010). R_m is the aggregate market excess return. R_{imc} is the return differential between investment good and consumption good producing sectors as in Papanikolaou (2011). Data are annual from 1966 to 2012. t-statistics in brackets are based on Newey-West standard errors. Regression intercepts are not reported.

Table 1.13: Demographic Shifts and Investment in Equipment, Software, and R&D

Panel A: Relation to future investment growth

	$\Delta I_{t,t+1}$	$\Delta I_{t,t+1}$	$\Delta I_{t,t+3}$	$\Delta I_{t,t+3}$	$\Delta I_{t-1,t}$	$\Delta I_{t-1,t}$
ω_t	7.52	6.61	23.38	14.75	2.45	2.83
	[4.50]	[2.51]	[6.72]	[2.97]	[1.44]	[1.23]
R^2 in %	3.06	59.17	8.04	64.01	0.35	58.27
FE	N	Y	N	Y	N	Y

Panel B: Relation to future investment rate

	I_{t+1}/K_t	I_{t+1}/K_t	$I_{t+1,t+3}/K_t$	$I_{t+1,t+3}/K_t$	I_t/K_{t-1}	I_t/K_{t-1}
ω_t	2.75	2.94	13.84	10.42	1.33	1.26
	[4.92]	[2.74]	[7.17]	[2.73]	[1.83]	[1.10]
R^2 in %	3.42	54.80	7.51	55.79	0.46	0.54
FE	N	Y	N	Y	N	Y

Notes: Table reports results from panel regressions using industry observations at the annual frequency from 1965 to 2014. FE is fixed effects. Columns with N are without, Y with industry and year fixed effects. t-statistics are based on standard errors clustered at the industry level. All coefficients are multiplied by 100. ω_t normalized to have unit standard deviation among all industry-year observations. ΔI is investment growth rate in equipment, software, and R&D. I/K is the quantity of investment divided by the quantity of fixed assets. $I_{t+1,t+3}$ is total investment from year $t+1$ to $t+3$. The left-hand variable is at the top of each column, the right-hand variable is ω_t where $\omega_t = \log(l_t^y/l_{t-1}^y) - \log(l_t^o/l_{t-1}^o)$. Regressions use 1,323 observations.

Table 1.14: Demographic Shifts and Investment in Structures

Panel A: Relation to future investment growth

	$\Delta I_{t,t+1}$	$\Delta I_{t,t+1}$	$\Delta I_{t,t+3}$	$\Delta I_{t,t+3}$	$\Delta I_{t-1,t}$	$\Delta I_{t-1,t}$
ω_t	2.14	1.78	9.31	1.26	-0.25	-1.48
	[1.41]	[0.27]	[2.69]	[0.16]	[-0.14]	[-0.43]
R^2 in %	0.02	68.51	0.30	58.62	0.00	70.32
FE	N	Y	N	Y	N	Y

Panel B: Relation to future investment rate

	I_{t+1}/K_t	I_{t+1}/K_t	$I_{t+1,t+3}/K_t$	$I_{t+1,t+3}/K_t$	I_t/K_{t-1}	I_t/K_{t-1}
ω_t	2.45	0.62	9.72	2.26	1.67	0.40
	[2.37]	[1.28]	[3.90]	[1.60]	[2.05]	[0.72]
R^2 in %	2.91	73.38	4.77	76.41	0.66	72.69
FE	N	Y	N	Y	N	Y

Notes: Table reports results from panel regressions using industry observations at the annual frequency from 1965 to 2014. FE is fixed effects. Columns with N are without, Y with industry and year fixed effects. t-statistics are based on standard errors clustered at the industry level. All coefficients are multiplied by 100. ω_t normalized to have unit standard deviation. ΔI is investment growth rate in structures. I/K is the quantity of investment divided by the quantity of fixed assets. $I_{t+1,t+3}$ is total investment from year $t+1$ to $t+3$. The left-hand variable is at the top of each column, the right-hand variable is ω_t where $\omega_t = \log(l_t^y/l_{t-1}^y) - \log(l_t^o/l_{t-1}^o)$. Regressions use 1,323 observations.

Table 1.15: Future Investment and Demographic Shifts

	ω_t			
$\Delta I_{t,t+3}$	0.21	0.13	0.22	0.12
	[3.50]	[1.84]	[3.19]	[1.62]
$z_{t,t+3}$			0.16	-0.02
			[2.42]	[-0.78]
$z_{t,t+3} \cdot \Delta I_{t,t+3}$		0.15		0.15
		[4.86]		[6.42]
R^2	0.64	0.66	0.65	0.67
FE	Y	Y	Y	Y

Notes: Table reports results from four regressions of ω_t on investment growth over the next three years ($\Delta I_{t,t+3}$), industry level IST over the three years ($z_{t,t+3}$), and an interaction term. Regressions include year and industry fixed effects. t-statistics are based on standard errors clustered at the industry level. ω_t, $z_{t,t+3}$, and $\Delta I_{t,t+3}$ are normalized to have unit standard deviation across all industry-year observations. ΔI is investment growth rate in equipment, software, and R& D. All regressions use 1,323 industry-year observations from 1966 to 2014.

Table 1.16: Parameters for Benchmark Calibration

α_k	0.2975	δ	0.01	μ_a	0.01/12
α_n	0.5525	s	0.03	σ_a	$0.035/\sqrt{12}$
e_y	0.77	c_n	4	μ_z	0.01/12
e_o	1.23	c_k	6	σ_z	$0.08/\sqrt{12}$
$\bar{w}^y$	0.015 e_y	c_z	-60	ρ_u	0.98
$\bar{w}^o$	0.015 e_o	r_f	0.0165/12	σ_u	0.05
τ_a^y	0.37	λ_a	25	ρ_z	0.98
τ_z^y	0.28	λ_z	5	$\sigma_{\tilde{z}}$	0.01
τ_a^o	0.68				
τ_z^o	-0.11				

Notes: α_k and α_n are the capital and labor share parameters in the production function. e_y and e_o ar the efficiency units of young and old employees. δ is the capital depreciation rate. s is the labor separation rate. $\bar{w}^y$ and $\bar{w}^o$ are level parameters for wages of young and old employees. τ_a^y, τ_z^y, τ_a^o, and τ_z^o are the parameters governing young and old wages to shocks to a and z^a. c_n and c_k are parameters of labor and capital adjustment costs. c_z is the parameter governing the impact of labor composition on capital adjustment costs. μ_a and μ_z are growth rates, σ_a and σ_z are conditional volatilities of aggregate productivity processes a and z^a. ρ_u and ρ_z are the persistence parameters, and σ_u and $\sigma_{\tilde{z}}$ are the conditional volatilities of firm-specific productivity processes u and $\tilde{z}$.

Table 1.17: Model Moments

Panel A: Real moments

	Data	Model		Data	Model		Data	Model
$\sigma(\Delta D_t)$	0.14	0.13	β_a^y	0.37	0.37	$\sigma(h/n)$ XS	0.26	0.13
$\mathbb{E}\left[w_t^y/w_y^o\right]$	0.61	0.61	β_z^y	0.28	0.28	$\sigma(h/n)$ TS	0.23	0.16
Wages/Output (value)	0.68	0.74	β_a^o	0.68	0.67	$\sigma(i/k)$ XS	0.21	0.17
Wages/Output (growth)	0.53	0.43	β_z^o	-0.11	-0.11	$\sigma(i/k)$ TS	0.23	0.18
Ψ_t^n/W_t^h	0.69	0.61	$\mathbb{E}[l_t^y/l_t^o]$	0.16	0.15	$\mathbb{E}[\omega]$ young	1.05	1.07
						$\mathbb{E}[\omega]$ old	0.94	0.96

Panel B: Asset pricing moments

	Data	Model		Data	Model
$\mathbb{E}\left[r_m - r_f\right]$	6.29	5.01	β_a^{yo}	-3.21	-1.93
$\sigma(r_m)$	18.10	14.46	β_z^{yo}	3.99	5.42
$\mathbb{E}\left[r_y - r_o\right]$	4.64	5.01	β_a^{vg}	3.97	5.95
$\mathbb{E}\left[r_v - r_g\right]$	6.04	5.17	β_z^{vg}	-1.18	-1.21
$\mathbb{E}\left[r_w - r_l\right]$	5.61	4.23	β_a^{wl}	-5.84	-2.18
$\mathbb{E}\left[r_e - r_c\right]$	4.48	3.60	β_z^{wl}	2.66	4.78
$corr(r_v - r_g, r_y - r_o)$	-0.28	-0.22			

Notes: $\sigma(\Delta D_t)$ is the annual volatility of aggregate dividends. $\mathbb{E}\left[w_t^y/w_y^o\right]$ is the average ratio of wages for young to old employees. Wages/Sales (value) and Wages/Sales (growth) is the average ratio of the wage bill to sales for the firms highest and lowest decile book-to-market deciles. Ψ_t^n/W_t^h is the average ratio of labor adjustment costs to the quarterly wages of new hires. β_a^y, β_z^y, β_a^o, β_z^y are defined in Table 1.20. $\mathbb{E}[l_t^y/l_t^o]$ is the average ratio of the number of young to old employees in the economy. $\sigma(h/n)$ XS and $\sigma(i/k)$ XS are the time series averages of the cross-sectional volatility in annual hiring and investment rates. $\mathbb{E}[\omega]$ young and $\mathbb{E}[\omega]$ old are the average values of ω for portfolios Y and O. $\mathbb{E}\left[r_m - r_f\right]$ is the annual aggregate market excess return in %. $\sigma(r_m)$ is the annual aggregate stock market volatility in %. $\mathbb{E}\left[r_y - r_o\right]$ is the average return differential in % between extreme quintile portfolios sorted on ω representing the YMO spread (young minus old). $\mathbb{E}\left[r_v - r_g\right]$ is the average return differential in % between extreme decile portfolios sorted on book-to-market ratio representing the value premium (value minus growth). $\mathbb{E}\left[r_w - r_l\right]$ is the average return differential in % between extreme quintile portfolios sorted on momentum (winners minus losers). $\mathbb{E}\left[r_e - r_c\right]$ is the average return differential in % between extreme decile portfolios sorted on gross hiring rate (expanding minus contracting). $corr(r_v - r_g, r_y - r_o)$ is the correlation between the monthly returns $r_v - r_g$ and $r_y - r_o$. β_a^{yo} and β_z^{yo} are the loadings of $r_y - r_o$ in annual contemporaneous regressions on Δa and Δz^a. β_a^{vg} and β_z^{vg} are the loadings of $r_v - r_g$ in annual contemporaneous regressions on Δa and Δz^a. β_a^{wl} and β_z^{wl} are the loadings of $r_w - r_l$ in annual contemporaneous regressions on Δa and Δz^a. β's are computed using normalized right-hand variables.

Table 1.18: Alternative Model Specifications

	Data	Baseline	Low wage	$c_z = 0$
$\mathbb{E}[r_m - r_f]$	6.29	5.01	3.12	4.15
$\sigma(r_m)$	18.10	14.46	7.67	8.12
$\mathbb{E}[r_y - r_o]$	4.64	5.01	4.15	0.00
$\mathbb{E}[r_v - r_g]$	6.04	5.17	1.42	1.21

Notes: $\mathbb{E}[r_m - r_f]$ is the annual aggregate market excess return in %. $\sigma(r_m)$ is the annual aggregate stock market volatility in %. $\mathbb{E}[r_y - r_o]$ is the average return differential in % between extreme quintile portfolios sorted on ω representing the YMO spread. $\mathbb{E}[r_v - r_g]$ is the average return differential in % between extreme decile portfolios sorted on book-to-market ratio representing the value premium. Low wage is a calibration with lower wages. $c_z = 0$ shuts off the impact of labor composition on capital adjustment costs.

Table 1.19: Demographics and Investment in the Model

Panel A: Predicting demographics				
	$\Delta I_{t,t+1}$	$\Delta I_{t,t+1}$	$\Delta I_{t,t+3}$	$\Delta I_{t,t+3}$
Data				
ω_t	6.61		14.75	
	[2.51]		[2.97]	
$\log(l_t^y/l_t^o)$		-1.66		-4.46
		[-1.03]		[-1.66]
Model				
ω_t	7.84		16.32	
	[6.12]		[7.14]	
$\log(l_t^y/l_t^o)$		1.02		0.24
		[1.31]		[0.68]
Panel B: Predicting investment growth				
	ω_{t+1}	ω_{t+1}	$\log(l_t^y/l_t^o)$	$\log(l_t^y/l_t^o)$
Data				
$\Delta I_{t-1,t}$	0.08		0.72	
	[1.65]		[7.10]	
$\Delta I_{t-3,t}$		0.03		0.66
		[0.60]		[8.40]
Model				
$\Delta I_{t-1,t}$	0.23		1.23	
	[0.14]		[4.54]	
$\Delta I_{t-3,t}$		-0.04		0.48
		[-0.45]		[6.41]

Notes: Table reports results from panel regressions using industry observations at the annual frequency from 1965 to 2014. Empirical regressions include industry and year fixed effects. t-statistics are based on standard errors clustered at the industry level. ω_t normalized to have unit standard deviation. ΔI is investment growth rate in equipment, software, and R&D. I/K is the quantity of investment divided by the quantity of fixed assets. $I_{t-3,t}$ is total investment from year $t-3$ to t. The left-hand variable is at the top of each column, the right-hand variable is in the first column. Regressions use 1,323 observations. Model-implied coefficients and t-statistics are averages across 500 simulations.

Table 1.20: Wages and Aggregate Shocks

i	β_a	β_z	$\bar{R}^2$
	k = 1		
Y	0.37	0.28	0.34
	[3.53]	[2.60]	
O	0.68	-0.11	0.40
	[8.32]	[-0.83]	
Y - O	-0.72	0.61	0.24
	[-2.97]	[3.69]	
	k = 5		
Y	0.71	0.52	0.49
	[3.09]	[4.23]	
O	1.63	0.00	0.58
	[6.90]	[-0.01]	
Y - O	-0.91	0.52	0.32
	[-3.29]	[3.52]	
	k = 7		
Y	0.92	0.51	0.68
	[4.31]	[5.49]	
O	1.89	0.03	0.70
	[7.29]	[0.19]	
Y - O	-0.97	0.48	0.40
	[-3.85]	[3.26]	

Notes: Table reports results from regressions of the form $\Delta \log(w^i_{t\to t+k}) = \beta_0 + \beta_a \Delta \log(a_{t\to t+k}) + \beta_z \Delta \log(z_{t\to t+k})$. $\Delta \log(w_{t\to t+k})$ is the k-year average wage growth per employee in the aggregate economy. $\Delta \log(a_{t\to t+k})$ and $\Delta \log(z_{t\to t+k})$ are total factor productivity growth and investment-specific technology growth in the corresponding k years, respectively. Rows i =Y (i =O) include results for young (old) employees. Y - O uses $\log(w^Y_{t\to t+k}) - \log(w^O_{t\to t+k})$ as the independent variable. Data are annual and span the period from 1965 to 2015. See Appendix A1.1 for details of data sources and construction.

Table 1.21: Model Moments with Unskilled Labor

	Data	Model		Data	Model
$\mathbb{E}[r_m - r_f]$	6.29	4.88	$\sigma(h/n)$ XS	0.26	0.11
$\sigma(r_m)$	18.10	14.01	$\sigma(h/n)$ TS	0.23	0.09
$\mathbb{E}[r_y - r_o]$	4.64	5.75	$\sigma(i/k)$ XS	0.21	0.16
$\mathbb{E}[r_v - r_g]$	6.04	3.49	$\sigma(i/k)$ TS	0.23	0.18
$\mathbb{E}[r_l - r_h]$	5.61	3.07	Wages/Sales (value)	0.68	0.65
$corr(r_v - r_g, r_y - r_o)$	-0.28	-0.16	Wages/Sales (growth)	0.53	0.54

Notes: See Table 1.17 for variable definitions.

Table 1.22: Model Moments with Transition From Young to Old

	Data	Model		Data	Model
$\mathbb{E}[r_m - r_f]$	6.29	5.17	$\sigma(h/n)$ XS	0.26	0.14
$\sigma(r_m)$	18.10	14.82	$\sigma(h/n)$ TS	0.23	0.15
$\mathbb{E}[r_y - r_o]$	4.64	6.75	$\sigma(i/k)$ XS	0.21	0.15
$\mathbb{E}[r_v - r_g]$	6.04	3.78	$\sigma(i/k)$ TS	0.23	0.16
$\mathbb{E}[r_l - r_h]$	5.61	3.32	Wages/Sales (value)	0.68	0.70
$corr(r_v - r_g, r_y - r_o)$	-0.28	-0.16	Wages/Sales (growth)	0.53	0.48

Notes: See Table 1.17 for variable definitions.

Table 1.23: Demographic Shifts and Investment Controlling for Past Investment Rate

Panel A: Relation to future investment growth

	$\Delta I_{t,t+1}$	$\Delta I_{t,t+1}$	$\Delta I_{t,t+3}$	$\Delta I_{t,t+3}$
ω_t	7.73	8.37	23.71	18.46
	[4.45]	[3.05]	[6.51]	[3.48]
$I_{t-1,t}/K_{t-1}$	-0.18	-0.74	-0.28	-1.51
	[-2.23]	[2.51]	[-1.18]	[-3.23]
R^2 in %	3.97	60.98	8.84	66.20
FE	N	Y	N	Y

Panel B: Relation to future investment rate

	I_{t+1}/K_t	I_{t+1}/K_t	$I_{t+1,t+3}/K_t$	$I_{t+1,t+3}/K_t$
ω_t	1.59	1.69	9.94	5.72
	[6.09]	[3.08]	[7.92]	[3.24]
$I_{t-1,t}/K_{t-1}$	0.83	0.73	2.65	2.14
	[8.58]	[2.51]	[8.18]	[7.14]
R^2 in %	64.28	87.41	57.08	85.25
FE	N	Y	N	Y

Notes: Table reports results from panel regressions using industry observations at the annual frequency from 1965 to 2014. FE is fixed effects. Columns with N are without, Y with industry and year fixed effects. t-statistics are based on standard errors clustered at the industry level. Coefficients on ω_t are multiplied by 100. ω_t normalized to have unit standard deviation. ΔI is investment growth rate in equipment, software, and R& D. I/K is the quantity of investment divided by the quantity of fixed assets. $I_{t+1,t+3}$ is total investment from year $t+1$ to $t+3$. The left-hand variable is at the top of each column, the right-hand variables are ω_t and $I_{t-1,t}/K_{t-1}$ where $\omega_t = \log(l_t^y/l_{t-1}^y) - \log(l_t^o/l_{t-1}^o)$. Regressions use 1,323 observations.

Table 1.24: Demographic Composition in Levels and Investment

Panel A: Relation to future investment growth

	$\Delta I_{t,t+1}$	$\Delta I_{t,t+1}$	$\Delta I_{t,t+3}$	$\Delta I_{t,t+3}$	$\Delta I_{t-1,t}$	$\Delta I_{t-1,t}$
$\log(l_t^y/l_t^o)$	2.31	-1.66	5.99	-6.46	2.72	-1.09
	[2.66]	[-1.03]	[2.52]	[-2.06]	[1.68]	[-1.05]
R^2 in %	2.18	59.79	5.06	63.69	2.93	58.63
FE	N	Y	N	Y	N	Y

Panel B: Relation to future investment rate

	I_{t+1}/K_t	I_{t+1}/K_t	$I_{t+1,t+3}/K_t$	$I_{t+1,t+3}/K_t$	I_t/K_{t-1}	I_t/K_{t-1}
$\log(l_t^y/l_t^o)$	5.10	0.38	18.71	0.97	5.13	0.71
	[5.30]	[0.45]	[6.65]	[0.31]	[6.64]	[0.72]
R^2 in %	32.18	71.37	37.25	72.98	32.60	71.02
FE	N	Y	N	Y	N	Y

Notes: Table reports results from panel regressions using industry observations at the annual frequency from 1965 to 2014. FE is fixed effects. Columns with N are without, Y with industry and year fixed effects. t-statistics are based on standard errors clustered at the industry level. All coefficients are multiplied by 100. ω_t normalized to have unit standard deviation. ΔI is investment growth rate in equipment, software, and R& D. I/K is the quantity of investment divided by the quantity of fixed assets. $I_{t+1,t+3}$ is total investment from year $t+1$ to $t+3$. The left-hand variable is at the top of each column, the right-hand variable is $\log(l_t^y/l_t^o)$. Regressions use 1,323 observations.

Table 1.25: Predicting Demographic Composition with Investment

Panel A: Predicting with investment growth				
	ω_{t+1}	ω_{t+1}	$\log(l_t^y/l_t^o)$	$\log(l_t^y/l_t^o)$
$\Delta I_{t-1,t}$	0.08		0.72	
	[1.65]		[7.10]	
$\Delta I_{t-3,t}$		0.03		0.66
		[0.60]		[8.40]
R^2 in %	60.16	60.01	72.47	79.85
Panel B: Predicting with investment rate				
I_t/K_{t-1}	0.15		6.64	
	[0.85]		[4.85]	
$I_{t-3,t}/K_{t-4}$		-0.02		2.19
		[-0.37]		[5.40]
R^2 in %	60.16	60.01	82.47	84.85

Notes: Table reports results from panel regressions using industry observations at the annual frequency from 1965 to 2014. Regressions include industry and year fixed effects. t-statistics are based on standard errors clustered at the industry level. ω_t normalized to have unit standard deviation. ΔI is investment growth rate in equipment, software, and R& D. I/K is the quantity of investment divided by the quantity of fixed assets. $I_{t-3,t}$ is total investment from year $t-3$ to t. The left-hand variable is at the top of each column, the right-hand variable is in the first column. Regressions use 1,323 observations.

Table 1.26: Future Investment, TFP, and Demographic Shifts

	ω_t			
$\Delta I_{t,t+3}$	0.21	0.23	0.22	0.23
	[3.50]	[1.84]	[3.19]	[1.62]
$a_{t,t+3}$			-0.03	-0.02
			[-0.74]	[-0.60]
$a_{t,t+3} \cdot \Delta I_{t,t+3}$		-0.09		-0.09
		[-3.07]		[2.61]
R^2	0.64	0.65	0.64	0.66
FE	Y	Y	Y	Y

Notes: Table reports results from four regressions of ω_t on investment growth over the next three years ($\Delta I_{t,t+3}$), industry level TFP over the three years ($a_{t,t+3}$), and an interaction term. Industry-level TFP data are from KLEMS. Regressions include year and industry fixed effects. t-statistics are based on standard errors clustered at the industry level. ω_t, $z_{t,t+3}$, and $\Delta I_{t,t+3}$ are normalized to have unit standard deviation across all industry-year observations. ΔI is investment growth rate in equipment, software, and R& D. All regressions use 1,323 industry-year observations from 1966 to 2014.

Table 1.27: Wage Dynamics

Panel A: Wage growth per employee						
	Young			Old		
	Y	M	O	Y	M	O
$t-2$	0.21	0.91	1.69	0.53	0.89	1.29
$t-1$	0.65	0.97	0.32	0.29	1.18	0.53
t	1.92	1.55	0.33	1.28	1.25	0.29
$t+1$	0.43	1.21	0.99	0.81	1.14	0.45
$t+2$	0.98	0.99	1.03	0.61	0.85	1.05
$t+3$	0.92	1.07	0.03	0.93	0.98	0.14
Panel B: Wage bill growth						
	Young			Old		
$t-2$	7.01	5.72	7.39	6.24	5.55	10.07
$t-1$	8.51	5.94	4.06	8.25	6.29	5.55
t	11.32	6.02	2.72	5.12	5.93	7.94
$t+1$	5.75	5.46	3.55	5.23	5.74	3.54
$t+2$	5.61	4.61	3.43	5.29	5.12	5.26
$t+3$	4.73	4.75	1.52	5.11	5.26	4.13

Notes: Panel A reports average wage growth per young and old skilled employee in industries in portfolio Y, M, O in year t. Panel B reports the same statistic for total wages of young and old skilled employees. The period covers from 1965 to 2015.

Table 1.28: Wage Costs

	Y	M	O
Panel A: Wage costs			
$t-2$	0.83	0.86	0.85
$t-1$	0.85	0.86	0.85
t	0.83	0.85	0.84
$t+1$	0.85	0.85	0.84
$t+2$	0.85	0.86	0.84
$t+3$	0.84	0.85	0.83
Panel B: Labor share			
$t-2$	0.50	0.52	0.50
$t-1$	0.48	0.53	0.48
t	0.47	0.52	0.48
$t+1$	0.48	0.51	0.48
$t+2$	0.47	0.52	0.47
$t+3$	0.48	0.51	0.47
Panel C: Operating leverage			
$t-2$	0.61	0.58	0.69
$t-1$	0.66	0.61	0.71
t	0.68	0.59	0.72
$t+1$	0.67	0.56	0.67
$t+2$	0.65	0.58	0.64
$t+3$	0.62	0.59	0.65

Notes: Panel A reports average ratio of total wages to total costs in industries in the time-t portfolio Y, M, O. Total costs are the sum of costs of goods sold, sales, general, and administrative expense, and wages. Panel B reports average labor shares computed as the ratio of wages to revenues in an industry. Panel C reports operating leverage computed as in Novy-Marx (2011). The period covers from 1965 to 2015.

Table 1.29: Workforce Composition Dynamics

	Y	M	O
ω_t	0.05	0.00	-0.06
ω_{t+1}	0.03	-0.01	-0.02
ω_{t+2}	0.02	0.00	-0.01
ω_t^s	0.03	0.03	0.03
$age_{ceo,t}$	61.43	62.33	62.56
$\Delta age_{ceo,t}$ in %	-0.69	-0.61	-0.66
Quit rate at t in%	2.28	2.16	2.38
Quit rate at $t+1$ in%	2.23	2.19	2.41
Quit rate at $t+2$ in%	2.32	2.21	2.30
Quit rate at $t+3$ in%	2.26	2.26	2.35

Notes: Table reports averages of variables related to workforce dynamics or portfolios Y, M, and O that are formed in year t based on ω_t. $\omega_t = \log(l_t^y/l_{t-1}^y) - \log(l_t^o/l_{t-1}^o)$ where l^y and l^o is the number of young and old skilled employees, respectively. $w_t^s = \log(l_t^s/l_{t-1}^s) - \log(l_t^u/l_{t-1}^u)$ where l_s and l_o is the number of skilled and unskilled employees, respectively. These data are in annual frequency from 1965 to 2015. age_{ceo} is the average age of CEOs from Execucomp for firms in the corresponding portfolios from 1990 to 2014. $\Delta age_{ceo,t}$ is the change in average CEO age from year $t-1$ to t. Quit rate is the ratio of monthly total quits to total number of employees in in industries computed using data from 2000 to 2015 from JOLTS.

Table 1.30: Portfolio Transitions

	Y	M	O
		1 year	
Y	0.42	0.44	0.13
M	0.14	0.73	0.13
O	0.12	0.51	0.37
		3 years	
Y	0.52	0.85	0.36
M	0.39	0.91	0.34
O	0.35	0.83	0.58
		5 years	
Y	0.67	0.93	0.37
M	0.53	0.95	0.48
O	0.38	0.92	0.68

Notes: Table reports portfolio transition rates. Rows correspond to portfolio in year t, column to the future portfolio. 3 years and 5 years report the probability of spending at least one year in the corresponding portfolio from $t+1$ to $t+3$ or $t+5$, respectively.

Table 1.31: Firm Expansions and Entry

	Y	M	O	Y - O
	Year $t-1$ to t			
Gains	2.12	1.43	1.87	0.25
Expansions	1.76	2.13	1.92	-0.16
Openings	2.45	1.17	1.32	1.13
Losses	1.32	0.76	0.96	0.87
Contractions	1.12	0.45	0.24	-1.12
Closings	2.76	3.31	1.34	1.42
	Year t to $t+1$			
Gains	2.48	1.14	1.92	0.56
Expansions	1.13	2.21	2.15	-1.02
Openings	6.42	-0.89	-2.34	8.76
Losses	1.32	0.38	2.13	-0.81
Contractions	0.34	0.27	1.97	-1.63
Closings	4.12	3.24	2.68	1.44

Notes: Table reports the annual growth rates of job gains and losses for the portfolio formation year and the subsequent year as reported in Business Employment Dynamics by BLS. Gains are reported for both expansions and openings. Losses are reported for both contractions and closings. Data are annual from 1990 to 2014. t-statistics are not reported for brevity. The only significant difference in the Y - O column with a t-statistic of 2.14 is openings from t to $t+1$.

Table 1.32: Cash-Flow Predictability (1-year)

Young-Old hiring spread				
	Y	M	O	Y - O
Δa	3.41	0.02	2.58	0.82
				[0.25]
Δz	2.12	0.96	-2.64	4.76
				[2.49]
R^2	0.01	-0.02	-0.01	0.05
Value versus growth				
	V	M	G	V - G
Δa	14.12	1.51	-2.66	16.78
				[2.99]
Δz	0.05	-0.09	-1.05	1.11
				[0.51]
R^2	0.13	-0.02	-0.02	0.17
Industry momentum				
	W	M	L	W - L
Δa	-8.62	2.74	5.14	-13.80
				[-2.17]
Δz	7.81	0.29	-2.02	9.82
				[2.61]
R^2	0.05	-0.01	0.01	0.15

Notes: Table reports results from predictive regressions of the form $\Delta d_{t+1} = \beta_0 + \beta_a \Delta a_{t-3,t} + \beta_z \Delta z_{t-3,t}$ where Δd_{t+1} is the annual log dividend growth, $\Delta a_{t-3,t}$ is the sum of annual log TFP shock from last three years, $\Delta z_{t-3,t}$ is the sum of annual log IST shock from last three years, $t-2$ is the portfolio formation year. Both of these aggregate shocks are normalized to have unit standard deviation. Coefficients are multiplied by 100. Portfolio dividends are computed following Bansal, Dittmar, Lundblad (2005). V, M, and G are high, medium, and low B/M portfolios where the cutoff values are 30% and 70% of a year's B/M distribution among NYSE stocks. W, M, and L are winner, medium, and loser industries based on last year's returns. t-statistics are based on Newey-West standard errors. The data period is from 1965 to 2015.

Table 1.33: Cash-Flow Predictability (3-year)

Young-Old hiring spread				
	Y	M	O	Y - O
β_a	-7.82	-6.92	-2.61	-5.21
				[-0.90]
β_z	25.15	7.15	3.83	21.31
				[3.97]
R^2	0.27	0.02	-0.01	0.25
Value versus growth				
	V	M	G	V - G
β_a	7.33	-6.83	-23.40	30.74
				[2.87]
β_z	11.84	9.64	2.59	9.25
				[0.94]
R^2	0.01	0.05	0.24	0.18
Industry momentum				
	W	M	L	W - L
β_a	-7.66	-7.18	-5.49	-2.17
				[-0.31]
β_z	31.13	13.37	-0.81	31.94
				[4.86]
R^2	0.30	0.14	-0.01	0.35

Notes: Table reports results from predictive regressions of the form $\Delta d_{t+1,t+3} = \beta_0 + \beta_a \Delta a_{t-3,t} + \beta_z \Delta z_{t-3,t}$ where $\Delta d_{t+1,t+3}$ is the annual log dividend growth over the next three years, $\Delta a_{t-3,t}$ is the sum of annual log TFP shock from last three years, $\Delta z_{t-3,t}$ is the sum of annual log IST shock from last three years. Both of these aggregate shocks are normalized to have unit standard deviation. Coefficients are multiplied by 100. Portfolio dividends are computed following Bansal, Dittmar, Lundblad (2005). V, M, and G are high, medium, and low B/M portfolios where the cutoff values are 30% and 70% of a year's B/M distribution among NYSE stocks. W, M, and L are winner, medium, and loser industries based on last year's returns. t-statistics are based on Newey-West standard errors. The data period is from 1965 to 2015.

Table 1.34: Cash-Flow Predictability (1-year) in subsamples

1990 - 2015				
	Y	M	O	Y - O
β_a	8.15	4.92	13.75	-2.59
				[-0.42]
β_z	2.51	-1.53	-9.29	11.80
				[2.31]
R^2	0.09	-0.02	0.15	0.05

1965 - 1990				
	Y	M	O	Y - O
β_a	-1.23	-2.92	-1.22	-0.00
				[-0.01]
β_z	1.07	2.34	-7.39	8.46
				[2.95]
R^2	-0.01	-0.01	0.04	0.04

Notes: Table reports results from predictive regressions of the form $\Delta d_{t+1,t+3} = \beta_0 + \beta_a \Delta a_{t-3,t} + \beta_z \Delta z_{t-3,t}$ where $\Delta d_{t+1,t+3}$ is the annual log dividend growth over the next three years, $\Delta a_{t-3,t}$ is the sum of annual log TFP shock from last three years, $\Delta z_{t-3,t}$ is the sum of annual log IST shock from last three years. Both of these aggregate shocks are normalized to have unit standard deviation. Coefficients are multiplied by 100. Portfolio dividends are computed following Bansal, Dittmar, Lundblad (2005). t-statistics are based on Newey-West standard errors. The data periods are from 1965 to 1990 and 1990 to 2015.

Table 1.35: Cash-Flow Predictability (3-year) in subsamples

1990 - 2015				
	Y	M	O	Y - O
β_a	-2.20	-12.75	7.42	-9.63
				[-0.94]
β_z	19.17	11.34	-0.35	19.52
				[3.97]
R^2	0.07	-0.02	-0.02	0.10

1965 - 1990				
	Y	M	O	Y - O
β_a	-1.05	-3.20	8.26	-9.31
				[-0.39]
β_z	12.61	2.80	-1.24	13.85
				[2.95]
R^2	0.14	-0.01	0.04	0.23

Notes: Table reports results from predictive regressions of the form $\Delta d_{t+1,t+3} = \beta_0 + \beta_a \Delta a_{t-3,t} + \beta_z \Delta z_{t-3,t}$ where $\Delta d_{t+1,t+3}$ is the annual log dividend growth over the next three years, $\Delta a_{t-3,t}$ is the sum of annual log TFP shock from last three years, $\Delta z_{t-3,t}$ is the sum of annual log IST shock from last three years. Both of these aggregate shocks are normalized to have unit standard deviation. Coefficients are multiplied by 100. Portfolio dividends are computed following Bansal, Dittmar, Lundblad (2005). t-statistics are based on Newey-West standard errors. The data periods are from 1965 to 1990 and 1990 to 2015.

Table 1.36: Rolling Factor Regressions with YMO

1-year			
α	3.39	4.77	4.18
	[3.10]	[3.25]	[2.68]
MKT	0.10	-0.01	-0.03
	[2.47]	[-0.26]	[-0.87]
SMB		0.05	0.07
		[0.90]	[1.28]
HML		-0.29	-0.25
		[-3.28]	[-2.26]
INV			0.12
			[0.99]
PROF			0.05
			[0.35]
3-year			
α	3.72	4.85	6.13
	[3.17]	[3.37]	[3.82]
MKT	0.11	0.03	0.01
	[2.78]	[1.08]	[0.08]
SMB		-0.03	-0.04
		[-0.70]	[-0.85]
HML		-0.21	-0.18
		[-3.42]	[-2.20]
INV			0.06
			[0.83]
PROF			-0.01
			[-0.12]

Notes: Table reports average coefficient estimates from rolling CAPM, Fama-French three-factor and five-factor models. Data are monthly from 1966 to 2015. t-statistics are based on GMM standard errors used to compute averages and rolling time series of factor loadings.

Table 1.37: Properties of ω

	Y	M	O	All
Mean	0.05	0.00	-0.06	-0.00
Median	0.04	-0.01	-0.07	-0.01
5%	-0.06	-0.12	-0.16	-0.12
95%	0.24	0.13	0.06	0.15
SD	0.11	0.09	0.09	0.10
Skewness	1.27	0.67	0.19	0.81

Notes: Table reports summary statistics for industry-year observations of $\omega_t = \log(l_t^y/l_{t-1}^y) - \log(l_t^o/l_{t-1}^o)$. Columns Y, M, and O include industries in the corresponding portfolios. The last column includes all industry-year observations. The data period is from 1966 to 2015.

Table 1.38: Alternative Measures of Demographic Shifts

	(1)	(2)
Panel A: YMO		
	4.41	3.96
	[2.78]	[2.38]
Panel B: Fama-French 5 factor		
α	6.01	4.85
	[3.01]	[2.98]
MKT	0.04	0.02
	[0.72]	[0.29]
SMB	-0.14	0.03
	[-1.07]	[0.46]
HML	-0.18	-0.26
	[-2.12]	[-2.41]
INV	0.05	-0.12
	[0.22]	[-0.94]
PROF	-0.03	0.02
	[-0.09]	[0.08]

Notes: Panel A reports YMO, the difference between the returns of young and old hiring portfolios, for alternative measures of ω_t:

(1) $\omega_t = l_t^y / l_{t-1}^y - l_t^o / l_{t-1}^o$,
(2) $\omega_t = (\Delta l_t^y - \Delta l_t^o)/(l_t^y + l_t^o)$.

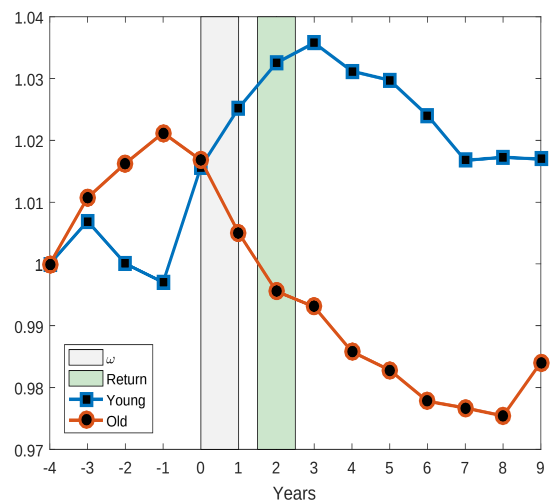
Panel B reports results from time-series regressions of YMO using the Fama and French (2015) 5-factor model. t-statistics in brackets are based on Newey-West standard errors.

Table 1.39: Sample of Industries in the Young Hiring Portfolio

1966 - 1975	1976 - 1980	1981 - 1990
Print & Publish	Measuring & control eq.	Chemicals
Telecom	Machinery	Transport eq.
Oil & mining	Print & publish	Construction
1996 - 2000	**2001 - 2010**	**2011 - 2015**
Telecom	Business services	Manufacturing & recycling
Electrical & optical eq.	Electrical & optical eq.	Transport eq.
Chemicals	Finance	Business services

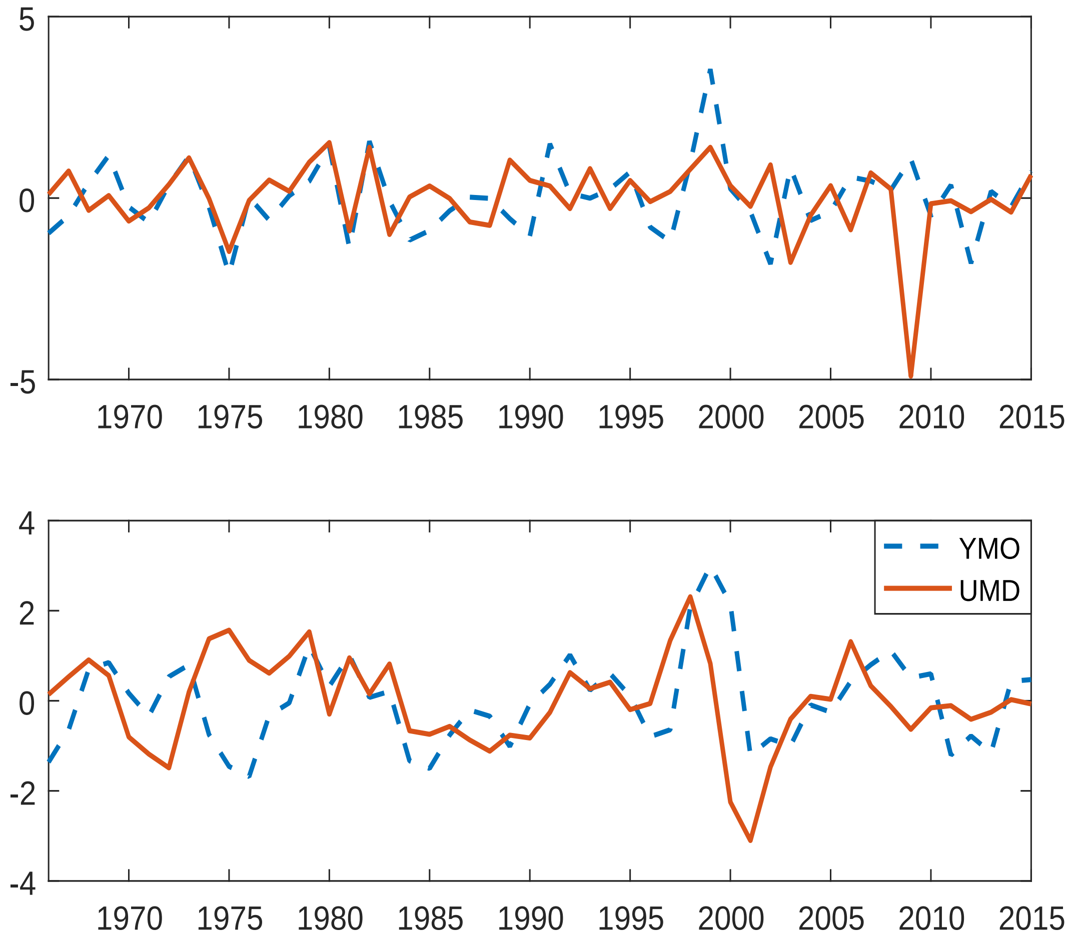
Notes: Table lists a sample of ISIC industries that spend the most time in the young portfolio in the corresponding periods.

Figure 1.1: Alternative Measure of Embodied Technology (IST Level)



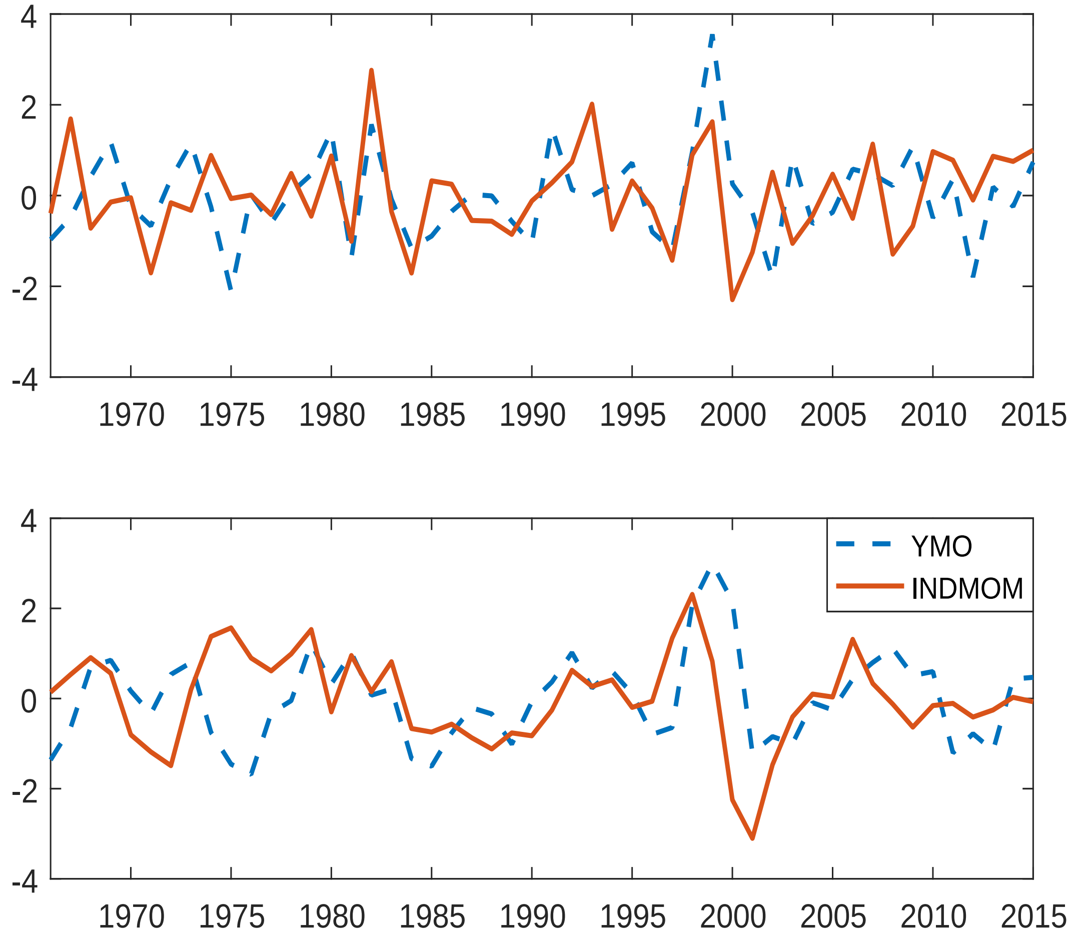
Notes: This figure replicates Figure 1.4 using the industry-level price index for value added from KLEMS rather than the consumption deflator.

Figure 1.2: UMD and YMO



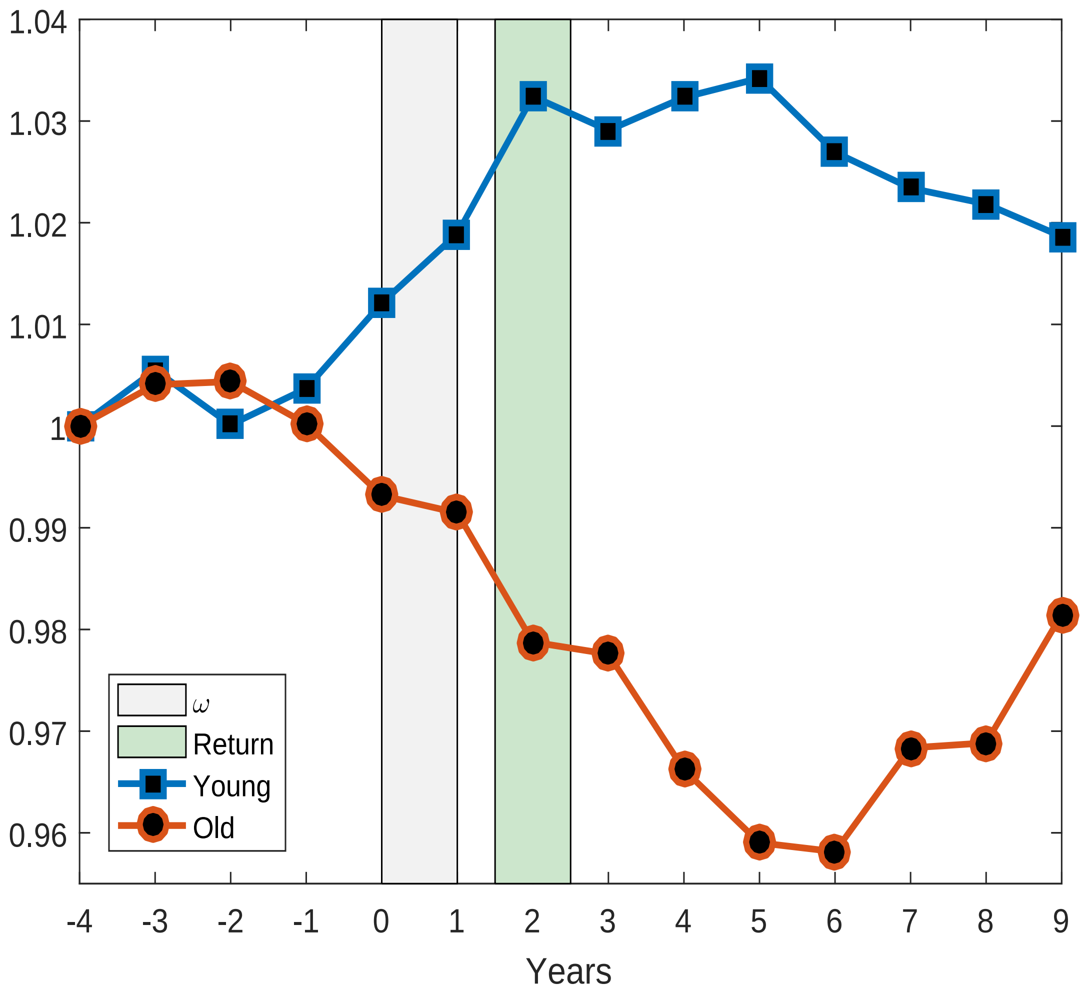
Notes: Figure plots the YMO spread and momentum factor (UMD) from Kenneth French's website. The top figure plots annual returns and the bottom figure plots three year average returns. All returns are normalized to have zero mean and unit standard deviation.

Figure 1.3: Industry Momentum



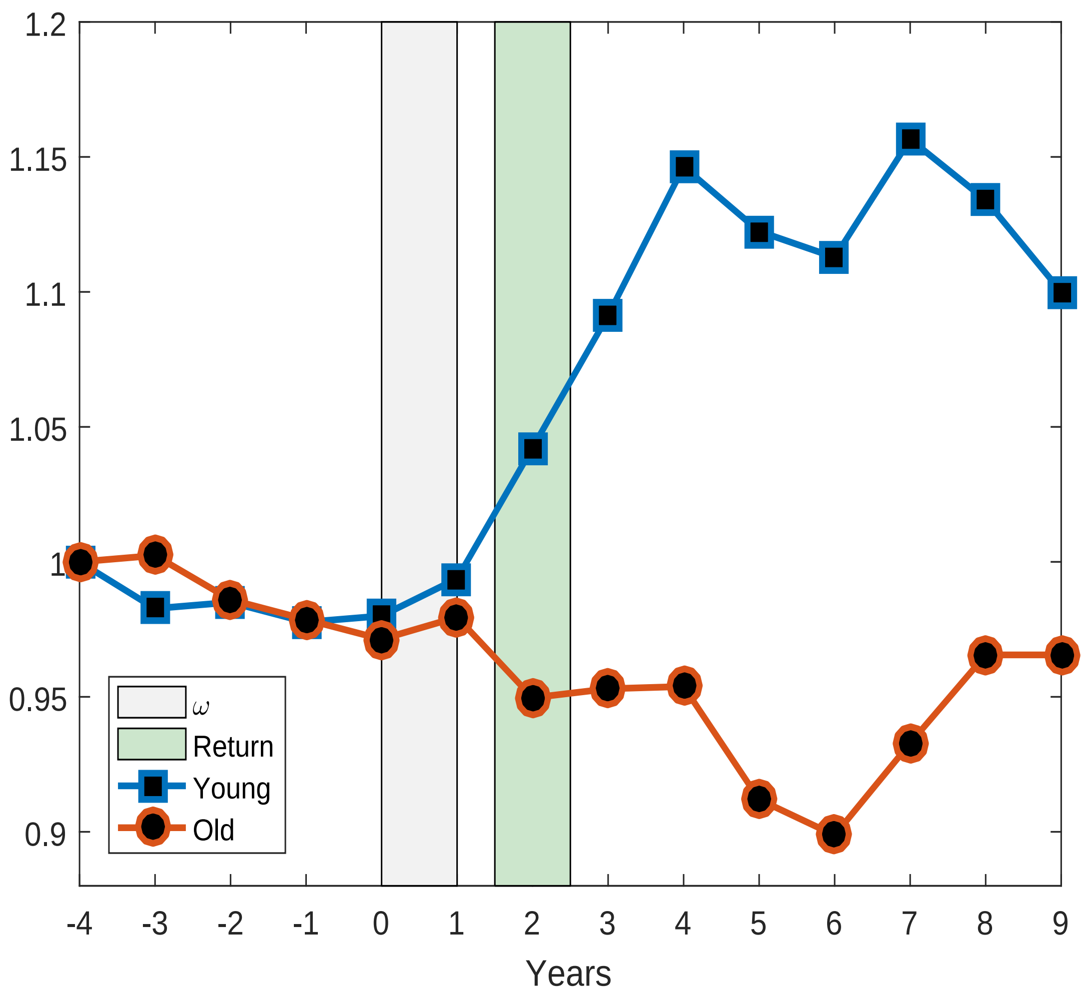
Notes: Figure plots the YMO spread and industry momentum returns (INDMOM) defined as the return differential between the six highest and lowest momentum industries among 30 industries from Kenneth French's website. The top figure plots annual returns and the bottom figure plots three year average returns. All returns are normalized to have zero mean and unit standard deviation.

Figure 1.4: Embodied Technology (IST Level)



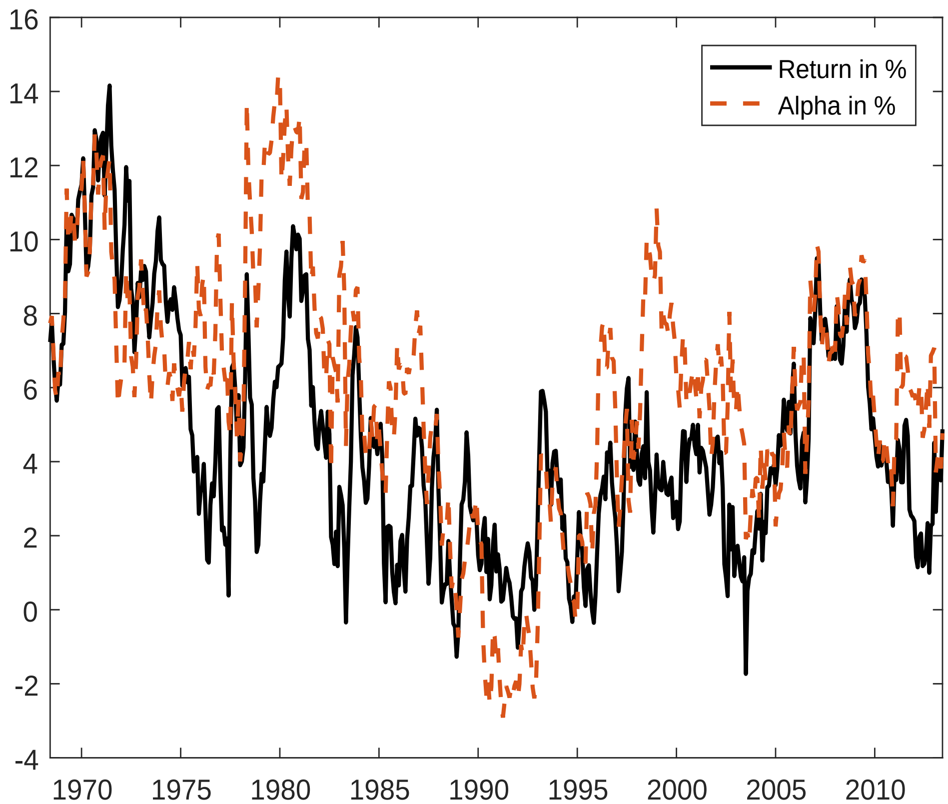
Notes: Figure plots the IST level for portfolio Y and O relative to the aggregate economy. The IST level is computed as the inverse of the relative price of investment at the industry level from KLEMS divided by the consumption deflator. Portfolio level quantities are computed using the average industry IST levels value-weighted by the quantity of investment. The IST level is normalized to one four years prior to portfolio formation. The gray area depicts the portfolio formation year, the green are depicts the year of return observation (YMO).

Figure 1.5: Investment



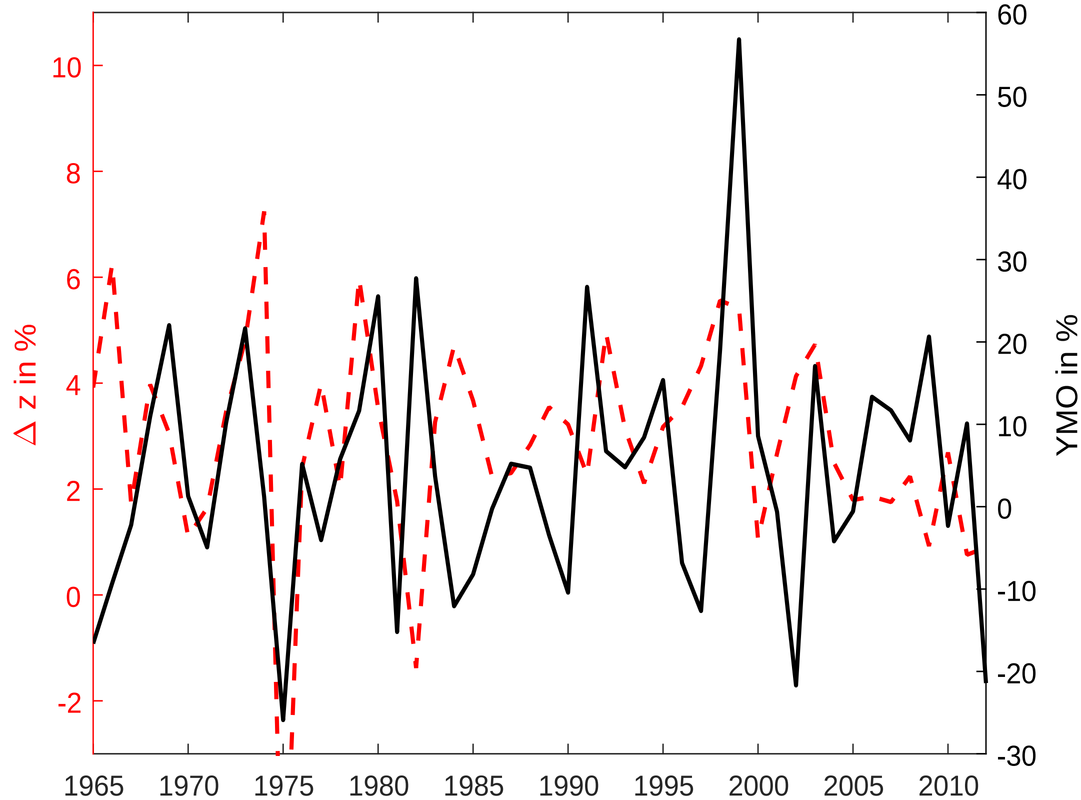
Notes: Investment for young and old hiring portfolios is constructed using quantity indices for equipment, software, and R&D from NIPA. Data are annual from 1965 to 2014. The gray area corresponds to the period where hiring measures are observed. The green area highlights the period expected returns are measured. Investment is normalized to one four years before portfolio formation, and the plotted series are computed using investment growth relative to the aggregate trend.

Figure 1.6: Five Year Average YMO Returns and Alphas



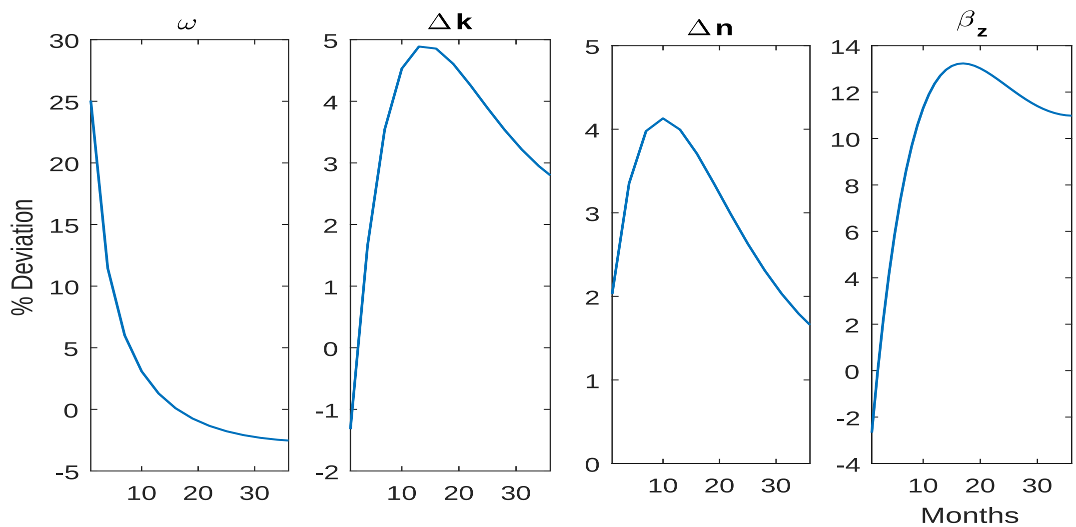
Notes: Figure plots 5-year average monthly YMO returns and rolling alphas from the Fama-French three-factor model.

Figure 1.7: Annual YMO Returns and IST shocks



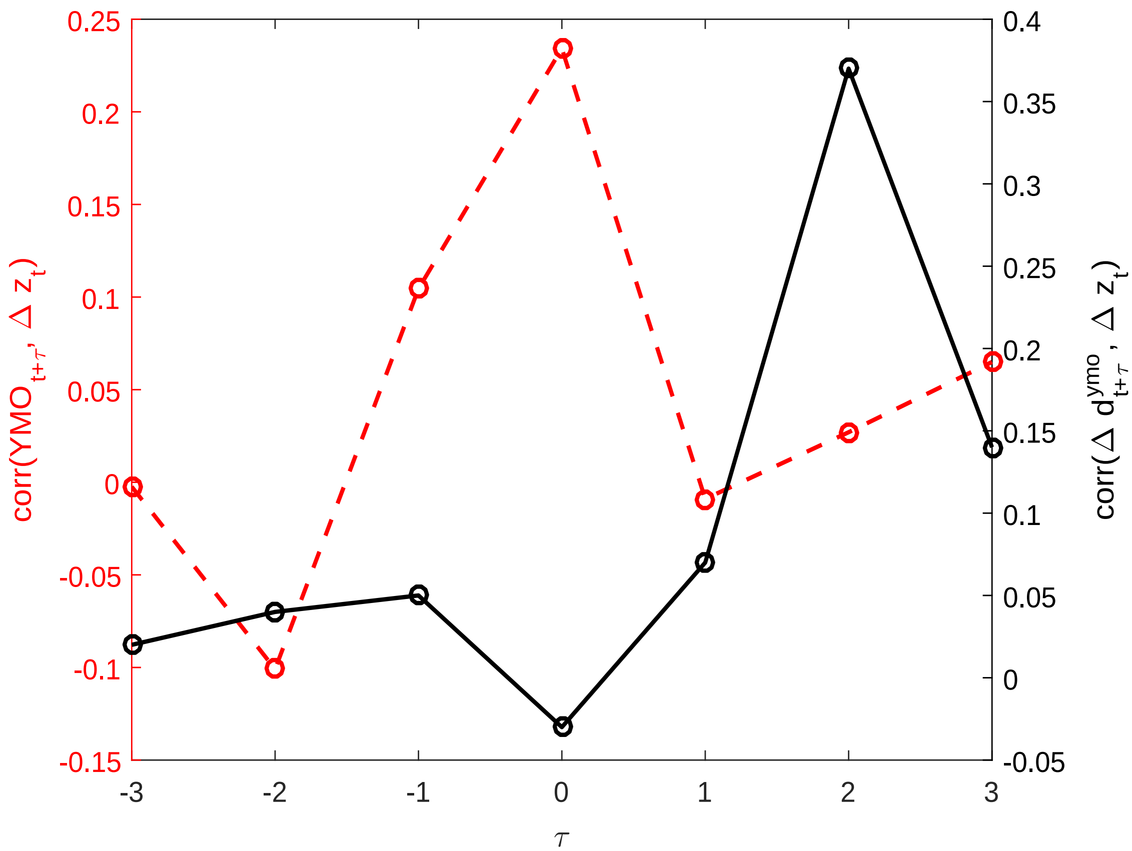
Notes: Figure plots the annual return differential between portfolios Y and O (solid line) and annual log IST shocks (dashed line). IST shocks are measured as the growth in the inverse of the relative price of equipment and software. The average of IST shocks in the post-1982 period is equated to the pre-1982 average.

Figure 1.8: Model Impulse response to a shock to $\tilde{z}$



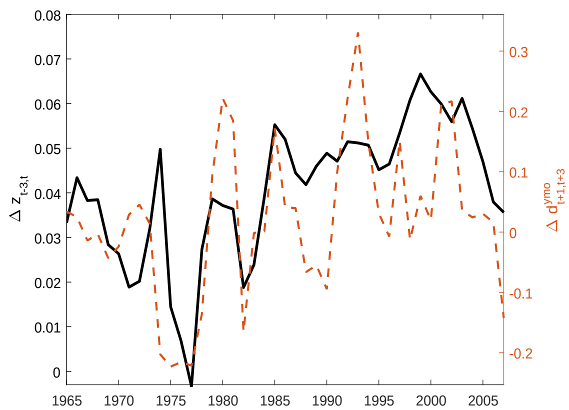
Notes: Figure plots the impulse response of Δk, Δn, ω to a one standard deviation shock to $\tilde{z}$. Δk is the growth of the capital stock, Δn is the growth of number of employees. ω is the hiring rate differential between young and old labor. β_z is the average 6-month loading of the stock return on the aggregate IST shock.

Figure 1.9: Correlations between Annual YMO Returns and IST shocks



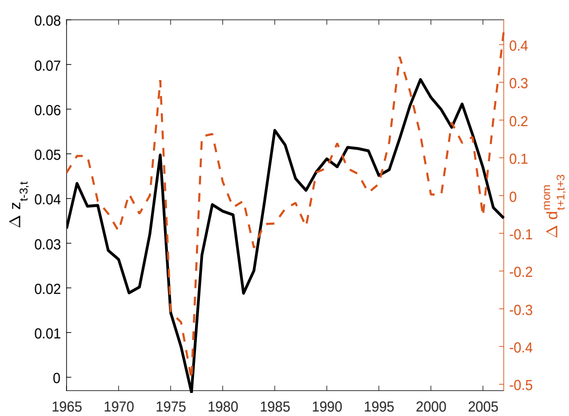
Notes: Figure plots the correlations of annual IST shocks with leads and lags of the the annual return differential between portfolios Y and O (dashed line line) and with the annual dividend growth differential between portfolios Y and O (solid line).

Figure 1.10: YMO cash-flows and IST shocks



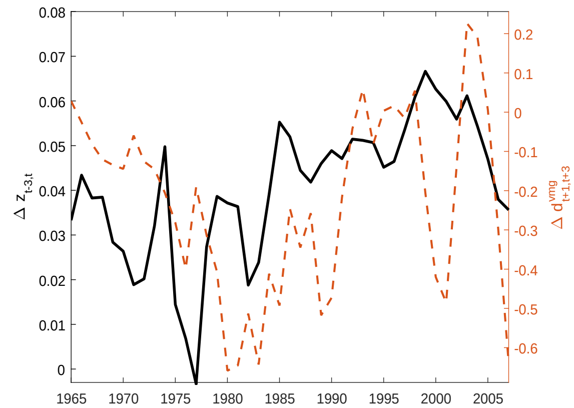
Notes: Figure plots the average of log IST shocks over the last three years (black line) and the log dividend growth differential between industries in portfolio Y and O (dashed line). IST shocks are measured as the growth in the inverse of the relative price of equipment and software.

Figure 1.11: INDMOM cash-flows and IST shocks



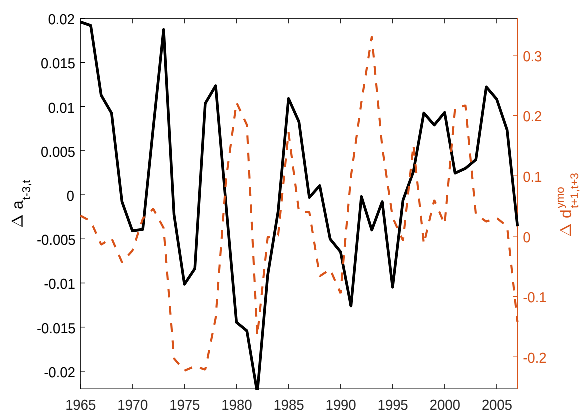
Notes: Figure plots the average of log IST shocks over the last three years (black line) and the log dividend growth differential between winner and loser industries used to compute industry momentum (dashed line). IST shocks are measured as the growth in the inverse of the relative price of equipment and software.

Figure 1.12: Value-growth cash-flows and IST shocks



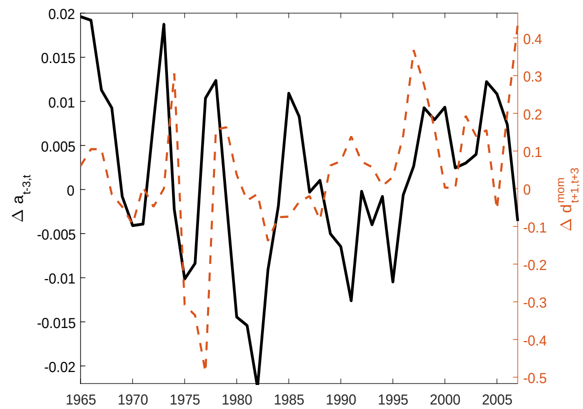
Notes: Figure plots the average of log IST shocks over the last three years (black line) and the log dividend growth differential between value and growth stocks based on the book-to-market ratio (dashed line). IST shocks are measured as the growth in the inverse of the relative price of equipment and software.

Figure 1.13: YMO cash-flows and TFP shocks



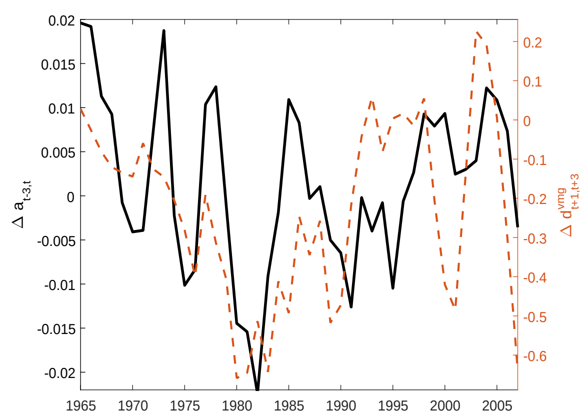
Notes: Figure plots the average of log TFP shocks over the last three years (black line) and the log dividend growth differential between industries in portfolio Y and O (dashed line).

Figure 1.14: INDMOM cash-flows and TFP shocks



Notes: Figure plots the average of log TFP shocks over the last three years (black line) and the log dividend growth differential between winner and loser industries used to compute industry momentum (dashed line).

Figure 1.15: Value-growth cash-flows and TFP shocks



Notes: Figure plots the average of log TFP shocks over the last three years (black line) and the log dividend growth differential between value and growth stocks based on the book-to-market ratio (dashed line).

CHAPTER 2 : Risk, Unemployment, and the Stock Market: A Rare-Event-Based Explanation of Labor Market Volatility

(with Jessica A. Wachter)

2.1. Introduction

The Diamond-Mortensen-Pissarides (DMP) model of search and matching offers an intriguing theory of labor market fluctuations based on the job creation incentives of employers (Diamond (1982), Pissarides (1985), Mortensen and Pissarides (1994)). When the contribution of a new hire to firm value decreases, employers reduce investment in hiring, decreasing the number of vacancies and, in turn, increasing unemployment. Due to the glut of job-seekers in the labor market, it becomes easier for employers to fill vacancies. Therefore, unemployment stabilizes at a higher level and the number of vacancies at a lower level. That is, labor market tightness (defined as the ratio of vacancies to unemployment) decreases until the payoff to hiring changes again.

While the mechanism of the DMP model is intuitive, a fundamental question remains unanswered: what causes job-creation incentives, and hence unemployment, to vary? The canonical DMP model and numerous successor models suggest that the driving force is labor productivity. However, explaining labor market volatility based on productivity fluctuations is difficult, because unemployment and vacancies are much more volatile than labor productivity (Shimer (2005)). Furthermore, unemployment does not track the movements of labor productivity, as is particularly apparent in the last three recessions. Rather, these recent data suggest a link between unemployment and stock market valuations (Hall (2015)).

In this paper, we make use of the DMP mechanism to explain the cyclical behavior of unemployment. However, rather than linking labor market tightness to productivity itself, we propose an equilibrium model in which fluctuations in labor market tightness arise from a small and time-varying probability of an economic disaster. Even if current labor productivity remains constant, disaster fears lower the job-creation incentives of firms. The labor market equilibrium shifts to a lower point on the vacancy-unemployment locus (the Beveridge curve), with higher unemployment and lower vacancy openings. At the same time, stock market valuations decline.

Our model generates a high volatility in unemployment and vacancies, along with a strong negative correlation between the two. This pattern of results accurately describes post-war U.S. data. We calibrate wage dynamics to match the behavior of the labor share in the data and find that matching the observed low response of wages to labor market conditions is crucial for both labor market volatility and realistic behavior of financial markets. Furthermore, the search and matching friction in the labor market and time-varying disaster risk result in a realistic equity premium and stock return volatility. Because the labor market and the stock market are driven by the same force, the price of the aggregate stock market and labor market tightness are highly correlated, while the correlation between labor productivity and tightness is realistically low.

Our paper is related to three strands of literature. First, since Shimer (2005) showed that the DMP model with standard parameter values implies small movements in unemployment and vacancies, a strand of literature has further developed the model to generate large responses of unemployment to aggregate shocks. In these papers, the aggregate shock driving the labor market is labor productivity. Hagedorn and Manovskii (2008) argue that a calibration of the model combining low bargaining power of workers with a high opportunity cost of employment can reconcile unemployment volatility in the DMP model with the data. Other papers suggest alternatives to the Nash bargaining assumption for wages (Hall (2005), Hall and Milgrom (2008), Gertler and Trigari (2009)). Compared with Nash bargaining, these alternatives render wages less responsive to productivity shocks. Thus a productivity shock can have a larger effect on job-creation incentives. Our paper departs from these in that we do not rely on time-varying labor market productivity as a driver of labor market tightness, which leads to a counterfactually high correlation between these variables. Furthermore, we also derive implications for the stock market, and explain the equity premium and volatility puzzles.[1]

Second, the present work relates to ones that embed the DMP model into the real business cycle framework, with a representative risk averse household that makes investment and consumption decisions. In the standard real business cycle (RBC) model (Kydland and Prescott (1982)), employment is driven by the marginal rate of substitution between consumption and leisure, and, because the labor market is frictionless, no vacancies go unfilled. Merz (1995) and Andolfatto (1996) observe that this model has counterfactual predictions for the correlation of productivity and employment, and build models that incorporate RBC features and search frictions in the labor market. These models capture the lead-lag relation between employment and productivity while having more realistic implications for wages and unemployment compared to the baseline RBC model. In this paper, we also document the lead-lag relation between productivity and employment in the period that this literature analyzes (1959 - 1988). However, our empirical analysis shows that this lead-lag relation is absent in more recent data. These papers do not study asset pricing implications.

Third, our paper is related to the literature on asset prices in dynamic production economies. These models build on the RBC framework, in which time-varying productivity determines consumption and dividend policy in equilibrium. In contrast, in an endowment economy, there is no aggregate technology for transfering consumption and dividends across periods and states.[2] Thus, relative to endowment economies, production economies face an additional hurdle in explaining the equity premium because of the agent's ability to smooth

[1]Other recent work connects time-variation in discount rates to unemployment. Eckstein, Setty, and Weiss (2015) solve a DMP model with risk-neutral investors and exogenous discount rates where labor and capital are complements. They show that volatility in corporate discount rates can account for volatility in unemployment. Hall (2015) conjectures that a DMP model in which discount rates rise in recessions can explain unemployment. He shows that, when an exogenous stochastic discount factor is estimated using the aggregate stock market, the resulting time series of unemployment tracks that in the data. Neither paper provides a general equilibrium model. Our results show that the connection between discount rates, recessions, and unemployment in a general equilibrium DMP model is more subtle than one might think (see Section 2.3.4).

[2]Of course, the agent in the endowment economy still optimally chooses consumption. However, asset prices adjust so that this optimal choice is equal to the endowment.

consumption (Kaltenbrunner and Lochstoer (2010), Lettau and Uhlig (2000)). Increasing risk aversion raises the equity premium in an endowment economy, but leads to even smoother consumption in production economy and thus very little fluctuation in marginal utility. Alternative preferences, such as habit formation can overcome this problem (Boldrin, Christiano, and Fisher (2001), Jermann (1998)) at the cost of highly volatile riskfree rates. Another approach is to allow for rare disasters. Barro (2006) and Rietz (1988) demonstrate that allowing for rare disasters in an endowment economy can explain the equity premium puzzle. Building on this work, Gourio (2012) studies the implications of time-varying disaster risk modeled as large drops in productivity and destruction of physical capital in a business cycle model with recursive preferences and capital adjustment costs. Gourio's model can explain the observed co-movement between investment and risk premia. However, unlevered equity returns have little volatility, and thus the premium on unlevered equity is low. This model can be reconciled with the observed equity premium by adding financial leverage, but the leverage ratio must be high in comparison with the data. As in RBC models with frictionless labor markets, Gourio's model does not explain unemployment. In the spirit of this literature, Petrosky-Nadeau, Zhang, and Kuehn (2013) build a model in which rare disasters arise endogenously through a series of negative productivity shocks. Like us, they build on the DMP model, but in a very different way. Their paper incorporates a calibration of Nash-bargained wages similar to Hagedorn and Manovskii (2008), leading to wages that are high and rigid. Moreover, their specification of marginal vacancy opening costs includes a fixed component, implying that it costs more to post a vacancy when labor conditions are slack and thus when output is low. Finally, they assume that workers separate from their jobs at a rate that is high compared with the data. The combination of a high separation rate, fixed marginal costs of vacancy openings and high and inelastic wages amplifies negative shocks to productivity and produces a negatively skewed output and consumption distribution. Like other DMP-based models described above, their model implies that labor market tightness is driven by productivity. Furthermore, while their model can match the equity premium, the fact that their simulations contain consumption disasters make it unclear whether the model can match the high stock market volatility and low consumption volatility that characterize the U.S. postwar data.

The paper is organized as follows. Section 2.2 provides empirical evidence about the relation between the labor market, labor productivity and the stock market. Section 2.3 presents the model and illustrates the mechanism in a simplified version. Section 2.4 discusses the quantitative results from the benchmark calibration and alternative calibrations. Section 2.5 concludes.

2.2. Labor Market, Labor Productivity and Stock Market Valuations

In the literature succeeding the canonical DMP model, labor productivity serves as the driving force behind volatility in unemployment and vacancies. Recent empirical work, however, has challenged this approach on the grounds that labor productivity is too stable compared with unemployment and vacancies, and that the variables are at best weakly correlated. In this section we summarize evidence on the interplay between unemployment, productivity and the stock market.

In Figure 2.1, we plot the time series of labor productivity Z and of the vacancy-unemployment ratio V/U, the variable that summarizes the behavior of the labor market in the DMP model.[3] Both variables are shown as log deviations from an HP trend.[4] Figure 2.1 shows the disconnect between the volatility of V/U and of productivity: labor productivity Z never deviates by more than 5 percent from trend, while, in contrast, V/U is highly volatile and deviates up to a full log point from trend. The lack of volatility in productivity as compared with labor market tightness is one challenge facing models that seek to explain unemployment using fluctuations in productivity.

Another challenge arises from the co-movement in these variables. Figure 2.1 shows that tightness and productivity did track each other in the recessions of the early 1960s and 1980s.

[3] All variables are measured in real terms. See Appendix A2.4 for a description of the data.

[4] Following Shimer (2005) we use a low-frequency HP filter with smoothing parameter 10^5 throughout to capture business cycle fluctuations. All results are robust to using an HP filter with smoothing parameter 1,600.

However, this contemporaneous correlation disappears in the later part of the sample. A striking example of this disconnect is the aftermath of the Great Recession, which simultaneously features a small productivity boom along with a labor-market collapse. Overall, the contemporaneous correlation between the variables is 0.10 as measured over the full sample, 0.47 until 1985 and -0.36 afterwards. There is some evidence that Z leads V/U; the maximum correlation between V/U and lagged Z occurs with a lag length of one year. However, this relation also does not persist in the second subsample; while the correlation over the full sample is 0.31, it is 0.62 in the subsample before 1985 and -0.09 after 1985.

While the data display little relation between unemployment and productivity, there is a relation between unemployment and the stock market.[5] We will focus on the ratio of stock market valuation P to labor productivity Z because P/Z has a clean counterpart in our model.[6] Figure 2.3 shows a consistently positive correlation between labor market tightness V/U and valuation P/Z. The correlation over the full sample is 0.47. In the period from 1986 to 2013, the correlation is 0.71. Moreover, like V/U, P/Z is volatile, with deviations up to 0.5 log points below trend. Figure 2.4 shows that vacancies V follow a similar pattern to V/U.

Why might labor markets be tightly connected with stock market valuations, but not with current productivity? In the sections that follow, we offer a model to answer this question.

2.3. Model

In Section 2.3.1 we review the DMP model of the labor market with search frictions. In Section 2.3.2, we use the DMP model with minimal additional assumptions to demonstrate a link between equity market valuations and labor market quantities. We confirm that this link holds in the data. In Section 2.3.3 we present a general equilibrium model that

[5] Our study focuses on the time-series relation between hiring and the stock market. Belo, Lin, and Bazdresch (2014) demonstrates a cross-sectional relation between required rates of return and hiring: firms that hire more appear to have lower risk premia. The same mechanism that we employ to explain the time series patterns can also account for this evidence.

[6] P/Z closely tracks Robert Shiller's cyclically adjusted price-earnings ratio (P/E), as shown in Figure 2.2. The correlation between the quarterly observations of these series is 0.97 for the period from 1951 to 2013.

explains labor market and stock market volatility in terms of time-varying disaster risk (we will examine the quantitative implications of this model in Section 2.4). In Section 2.3.4 we give closed-form solutions in a special case of the model in which disaster risk is a constant. This special case gives intuition for how disaster risk affects labor market quantities and prices in financial markets.

2.3.1. Search frictions

The labor market is characterized by the DMP model of search and matching. The representative firm posts a number of job vacancies $V_t \geq 0$. The hiring flow is determined according to the matching function $m(N_t, V_t)$, where N_t is employment in the economy and lies between 0 and 1. We assume that the matching function takes the following Cobb-Douglas form:

$$m(N_t, V_t) = \xi(1 - N_t)^{\eta} V_t^{1-\eta}, \tag{2.1}$$

where ξ is matching efficiency and η is the unemployment elasticity of the hiring flow. As a result, the aggregate law of motion for employment is given by

$$N_{t+1} = (1 - s)N_t + m(N_t, V_t), \tag{2.2}$$

where s is the separation rate.[7] Define labor market tightness as follows:

$$\theta_t = \frac{V_t}{U_t}.$$

The unemployment rate in the economy is given by $U_t = 1 - N_t$. Thus the probability of finding a job for an unemployed worker is $m(N_t, V_t)/U_t = \xi\theta_t^{1-\eta}$. Accordingly, we define the job-finding rate $f(\theta_t)$ to be

$$f(\theta_t) = \xi\theta_t^{1-\eta}. \tag{2.3}$$

[7] The assumption of $V_t > 0$ implies that the maximum drop in employment level is s.

Analogously, the probability of filling a vacancy posted by the representative firm is $m(N_t, V_t)/V_t = \xi\theta_t^{-\eta}$ which corresponds to the vacancy-filling rate $q(\theta_t)$ in the economy:

$$q(\theta_t) = \xi\theta_t^{-\eta}. \tag{2.4}$$

It follows from (**??**) and (2.4) that the job-finding rate is increasing, and the vacancy-filling rate decreasing, in the vacancy-uenployment ratio. In times of high labor market tightness, namely, when the vacancy rate is high and/or the unemployment rate is low, the probability of finding a job per unit time increases, whereas filling a vacancy takes more time.

Finally, the representative firm incurs costs κ_t per vacancy opening. As a result, aggregate investment in hiring is $\kappa_t V_t$.

2.3.2. Equity Valuation and the Labor Market

In this section we derive an equibrium restriction that links the value of the stock market to conditions in the labor market. To establish this link, we make use of the framework in Section 2.3.1 but with minimal additional assumptions.

Let M_{t+1} denote the representative household's stochastic discount factor. Consider a representative firm which produces output given by

$$Y_t = Z_t N_t, \tag{2.5}$$

where Z_t is the non-negative level of aggregate labor productivity. Assume that labor productivity follows the process

$$\log Z_{t+1} = \log Z_t + \mu + x_{t+1}, \tag{2.6}$$

where, for now, we leave x_{t+1} unspecified; it can be any stationary process. Let $W_t = W(Z_t, N_t, V_t)$ denote the aggregate wage rate. The firm pays out dividends D_t, which is what remains from output after paying wages and investing in hiring:

$$D_t = Z_t N_t - W_t N_t - \kappa_t V_t. \tag{2.7}$$

The firm then maximizes the present value of current and future dividends

$$\max_{\{V_{t+\tau}, N_{t+\tau+1}\}_{\tau=0}^{\infty}} \mathbb{E}_t \sum_{\tau=0}^{\infty} M_{t+\tau} D_{t+\tau} \tag{2.8}$$

subject to

$$N_{t+1} = (1-s)N_t + q(\theta_t)V_t, \tag{2.9}$$

where $q(\theta_t)$ is given by (2.4). The firm takes θ_t and W_t as given in solving (2.8). The economy is therefore subject to a congestion externality. By posting more vacancies, firms raise the aggregate V_t, therefore increasing θ_t and lowering the probability that any one firm will be able to hire.

The following result establishes a general relation between the stock market and the labor market.

Theorem 1. *Assume the production function (2.5) and that the firm solves (2.8). Then the ex-dividend value of the firm is given by*

$$P_t = \frac{\kappa_t}{q(\theta_t)} N_{t+1}, \tag{2.10}$$

and the equity return equals

$$R_{t+1} = \frac{(1-s)\frac{\kappa_{t+1}}{q(\theta_{t+1})} + Z_{t+1} - W_{t+1}}{\frac{\kappa_t}{q(\theta_t)}}. \tag{2.11}$$

Furthermore, if $\kappa_t = \kappa Z_t$ for fixed κ, then

$$\frac{P_t}{Z_t} = \frac{\kappa}{q(\theta_t)} N_{t+1}. \tag{2.12}$$

Proof. See Appendix A2.1. □

Some notation is helpful in understanding this theorem. Let l_t denote the Lagrange multiplier on the firm's hiring constraint (2.9). We can think of l_t as the value of a worker inside the firm at time $t+1$. In deciding how many vacancies to post at time t, the firm equates the marginal benefit of an additional worker with marginal cost. Because the probability of filling a vacancy with a worker is $q(\theta_t)$ (see Section 2.3.1), the marginal benefit is $l_t q(\theta_t)$ while the marginal cost is simply the cost of opening a vacancy, κ_t. Thus a condition for optimality is:

$$\kappa_t = l_t q(\theta_t). \tag{2.13}$$

It follows that $l_t = \kappa_t / q(\theta_t)$, and furthermore, that the value of the firm equals the number of workers employed multiplied by the value of each worker. This is what is shown in (2.10).

Equation 2.11 has a related interpretation. The $t+1$ return on the investment of hiring a worker is the value of the worker employed in the firm at time $t+2$ (multiplied by the probability that the worker remains with the firm), plus productivity minus the wage, all divided by the value of the worker at time $t+1$. Note that the previous discussion implies that the value of the worker employed at $t+1$ is $\frac{\kappa_t}{q(\theta_t)}$.

Equation 2.12 follows directly from (2.10) and from the assumption that the cost of posting a vacancy is proportional to productivity (given our assumption of a nonstationary component to productivity, this implies a balanced growth path). We can evaluate (2.12) empirically. We take the historical time series of the price-productivity ratio and of N_{t+1} (equal to one minus the unemployment rate). Given standard parameters for the matching function (discussed further below), this implies, by way of (2.12), a time series for the vacancy-unemployment ratio θ_t. Figure 2.5 shows that the resulting ratio of vacancies to unemployment lines up closely with its counterpart in the data.

2.3.3. *General equilibrium*

In this section, we extend our previous results to general equilibrium. Theorem 1 still holds, but the general equilibrium model allows us to model the underlying source of employment and stock price fluctuations.

2.3.3.1. *The Representative Household*

Following Merz (1995) and Gertler and Trigari (2009), we assume that the representative household is a continuum of members who provide one another with perfect consumption insurance. We normalize the size of the labor force to one.[8] The household maximizes utility over consumption, characterized by the recursive utility function introduced by Kreps and Porteus (1978) and Epstein and Zin (1989b):

$$J_t = \left[C_t^{1-\frac{1}{\psi}} + \beta \left(\mathbb{E}_t \left[J_{t+1}^{1-\gamma} \right] \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right]^{\frac{1}{1-\frac{1}{\psi}}}, \tag{2.14}$$

where β is the time discount factor, γ is relative risk aversion and ψ is the elasticity of intertemporal substitution (EIS). In case of $\gamma = 1/\psi$, recursive preferences collapse to power utility.

The recursive utility function implies that, assuming optimal consumption, the stochastic discount factor takes the following form:

$$M_{t+1} = \beta \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{1}{\psi}} \left(\frac{J_{t+1}}{\mathbb{E}_t \left[J_{t+1}^{1-\gamma} \right]^{\frac{1}{1-\gamma}}} \right)^{\frac{1}{\psi}-\gamma}. \tag{2.15}$$

[8]This assumption implies that our model focuses on the transition between employment and unemployment rather than between in and out of labor force.

2.3.3.2. Wages

The canonical DMP model assumes that wages are determined by Nash bargaining between the employer and the jobseeker. Both parties observe the surplus of job creation; the fraction received by the jobseeker is determined by his bargaining power. Pissarides (2000) shows that the Nash-bargained wage, W_t^N, is given by

$$W_t^N = (1 - B)b_t + B(Z_t + \kappa_t \theta_t), \tag{2.16}$$

where $0 \leq B \leq 1$ represents the worker's bargaining power and b_t is the flow value of unemployment.[9] The Nash-bargained wage is a weighted average of two components: the opportunity cost of employment and the contribution of the worker to the firm's profits. If the bargaining power of the worker is high, the firm has to pay a higher fraction of the output the worker produces as wage, as well as the foregone costs from not having to hire.

The Nash-bargained wage is a useful benchmark. However, it implies wages that are unrealistically responsive to changes in labor market conditions (see Section 2.2). This is a well-known problem in the literature on labor market search. Hall (2005) proposes a rule that partially insulates wages from tightness in the labor market. Let

$$W_t = \nu W_t^N + (1 - \nu) W_t^I, \tag{2.17}$$

where

$$W_t^I = (1 - B)b_t + B(Z_t + \kappa_t \bar{\theta}). \tag{2.18}$$

The parameter ν controls the degree of tightness insulation.[10] With $\nu = 1$, we are back in the Nash bargaining case. With $\nu = 0$, wages do not respond to labor market tightness.

[9]The canonical Nash-bargained wage equation holds in our model. See Petrosky-Nadeau, Zhang, and Kuehn (2013) for the proof in a similar setting.

[10]Hall (2005) specifies W_t^I as constant and productivity as stationary. In our setting with non-stationary productivity, W_t^I must be proportional to Z_t to allow for balanced growth. In Section 2.2, we show that, in the data, wages are responsive to Z_t but not to θ_t.

The resulting wage remains sensitive to productivity but loses some of its sensitivity to tightness. Furthermore, this formulation allows a direct comparison between versions of the model with and without tightness insulated wages. Hall and Milgrom (2008) provides a microfoundation for (2.17).

To have a balanced-growth path, we will assume $b_t = bZ_t$ (recall that $\kappa_t = \kappa Z_t$, see Section 2.3.2). Besides being necessary from a modeling perspective, it is also realistic to link unemployment benefits (broadly defined) with productivity: as Chodorow-Reich and Karabarbounis (2015) show using micro data, the time benefits of unemployment are an empirically large fraction of total unemployment benefits. The importance of these time benefits imply that, in the data, total benefits to unemployment are procyclical.

2.3.3.3. Technology and the Representative Firm

The representative firm produces output Y_t with technology $Z_t N_t$ given in (2.5). In normal times, $\log Z_t$ follows a random walk with drift. In every period, there is a small and time-varying probability of a disaster.[11] Thus,

$$\log Z_{t+1} = \log Z_t + \mu + \epsilon_{t+1} + d_{t+1}\zeta_{t+1}, \tag{2.19}$$

where $\epsilon_t \overset{iid}{\sim} N(0, \sigma_\epsilon^2)$,

$$d_{t+1} = \begin{cases} 1 & \text{with probability } \lambda_t \\ 0 & \text{with probability } 1 - \lambda_t. \end{cases}$$

and where $\zeta_t < 0$ gives the decline in log productivity, should a disaster occur.[12] We assume the log of the disaster probability λ_t follows an autoregressive process which (for convenience) is independent of the shocks to productivity. That is,

$$\log \lambda_t = \rho_\lambda \log \lambda_{t-1} + (1 - \rho_\lambda) \log \bar{\lambda} + \epsilon_t^\lambda, \tag{2.20}$$

[11] See Gabaix (2012), Gourio (2012) and Wachter (2013).

[12] The distribution of ζ_t is time-invariant and therefore independent of all other shocks.

where $\bar{\lambda}$ is the mean log probability, ρ_λ is the persistence, and $\epsilon_t^\lambda \overset{iid}{\sim} N(0, \sigma_\lambda^2)$. In solving the model, we approximate this process using a finite-state Markov chain with all nodes smaller than one (see Table 2.3).

Following the literature on disasters and asset pricing (e.g. Barro (2006), Gourio (2012)) we interpret a disaster broadly as any event that results in a large drop in GDP and consumption. Major wars, for example, lead to a large destruction in the capital stock, rendering existing workers less productive. A disruption in the financial system, or a major change in economic institutions could also lead to sharply lower output per worker.

2.3.3.4. Equilibrium

In equilibrium, the representative household holds all equity shares of the representative firm. The representative household consumes the output $Z_t N_t$ net of investment in hiring $\kappa_t V_t$, and the value of non-market activity $b_t(1 - N_t)$ achieved by the unemployed members:

$$C_t = Z_t N_t + b_t(1 - N_t) - \kappa_t V_t. \tag{2.21}$$

Note that consumption includes firm wages and dividends; the definition of dividends in (2.7) shows that the sum of wages and dividends amounts to $Z_t N_t - \kappa_t V_t$. The household also consumes the flow value of unemployment. This implies that we are treating this flow value primarily as home production as opposed to unemployment benefits (which would be a transfer that would net to zero).[13] To summarize, households maximize (2.14), subject to the budget constraint (2.21) and the law of motion for N_t (2.9), where θ is taken as given. The fact that the household owns all equity shares implies that the optimal investment in hiring is also that which solves the firm's problem.

The proportionality assumptions on vacancy costs κ_t and the flow value of unemployment

[13] This is consistent with the results of Chodorow-Reich and Karabarbounis (2015) as discussed in Section 2.3.3.2. Changing to the alternative assumption that these benefits net to zero, however, does not impact our results. To ensure that our model-data comparison is valid, when quantitatively assessing the model we report the model-implied dynamics of consumption from dividends and wages, namely, $Z_t N_t - \kappa_t V_t$, as this is what is measured in consumption data.

b_t in productivity Z_t imply that we can write:

$$C_t = Z_t N_t + bZ_t(1 - N_t) - \kappa Z_t V_t. \tag{2.22}$$

Therefore, we can define consumption normalized by productivity, $c_t = C_t/Z_t$, as

$$c_t = N_t + b(1 - N_t) - \kappa V_t. \tag{2.23}$$

In equilibrium, the value function J_t is determined by productivity, the disaster probability and the employment level. That is, $J_t = J(Z_t, \lambda_t, N_t)$. Given our assumptions on productivity and the homogeneity of utility, the value function takes the form

$$J(Z_t, \lambda_t, N_t) = Z_t j(\lambda_t, N_t), \tag{2.24}$$

where we refer to $j(\lambda_t, N_t)$ as the *normalized value function.* The normalized value function solves

$$j(\lambda_t, N_t) = \max_{c_t, V_t} \left[c_t^{1-\frac{1}{\psi}} + \beta \left(\mathbb{E}_t \left[e^{(1-\gamma)(\mu+\epsilon_{t+1}+d_{t+1}\zeta_{t+1})} j(\lambda_{t+1}, N_{t+1})^{1-\gamma} \right] \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right]^{\frac{1}{1-\frac{1}{\psi}}}, \tag{2.25}$$

subject to (2.23) and (2.9). This normalization implies that we can solve for all quantities of interest as functions of two stationary state variables, λ_t and N_t.

2.3.4. Comparative Statics in a Model with Labor Search and Constant Disaster Probability

Before exploring the quantitative implications of our full model in Section 2.4, we consider the simpler case of constant disaster probability. We show that the economy is isomorphic to one without disasters but with a different time discount factor. When the EIS is greater than one, the effect of disasters is to make the agent less patient and lead him to invest less in hiring. An analogous isomorphism is present in the models of Gabaix (2011) and Gourio (2012). Furthermore, stock prices are decreasing, and unemployment increasing as a function of the disaster probability, provided that the EIS is greater than one. The closed-form solutions allow us to give intuition for these results, which will carry over to the dynamic results in Section 2.4.

To derive closed-form solutions, we replace the random variable $d_{t+1}\zeta_{t+1}$ with a compound Poisson process with intensity $\tilde{\lambda}$. At our parameter values, the difference between the probability of a disaster λ and the intensity $\tilde{\lambda}$ is negligible, and we continue to refer to $\tilde{\lambda}$ as the disaster probability. Unless otherwise stated, proofs are contained in Appendix A2.2.

Theorem 2. *Assume that disaster risk is constant. The value function in a model with labor search and disasters is the same as the value function in a model without disasters but with a different time-discount factor. That is, the normalized value function solves*

$$j(\tilde{\lambda}, N_t)^{1-\frac{1}{\psi}} = c_t^{1-\frac{1}{\psi}} + \hat{\beta}(\tilde{\lambda}) \left(\mathbb{E}_t \left[e^{(1-\gamma)(\mu+\epsilon_{t+1})} j(\tilde{\lambda}, N_{t+1})^{1-\gamma} \right] \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}}, \tag{2.26}$$

with the time-discount factor $\hat{\beta}(\tilde{\lambda})$ defined by

$$\log \hat{\beta}(\tilde{\lambda}) = \log \beta + \frac{1-\frac{1}{\psi}}{1-\gamma} \left(\mathbb{E}\left[e^{(1-\gamma)\zeta} \right] - 1 \right) \tilde{\lambda}, \tag{2.27}$$

Moreover, $\hat{\beta}(\tilde{\lambda})$ is decreasing in $\tilde{\lambda}$ if and only if $\psi > 1$.

Note that (2.26) recursively defines the normalized value function in an economy without disaster risk. Theorem 2 shows that an economy with disasters is equivalent to one without, but with a less patient agent when the EIS $\psi > 1$ and a more patient agent when $\psi < 1$. As this statement suggests, the change to the time-discount factor due to disasters reflects a trade-off between an income and a substitution effect. On the one hand, the presence of disasters lead the agent to want to save (the income effect). But the mechanism that the agent has to shift consumption, namely, investing in hiring, becomes less attractive because there is a greater chance that the workers will not be productive (the substitution effect). When $\psi > 1$, the substitution effect dominates, and the agent, in effect, becomes less patient.

We can also see the effect of the probability of disaster on the riskfree rate and on the equity premium. In the case with constant λ_t, these equations turn out to be the same as in an endowment economy model (Tsai and Wachter (2015)).

Lemma 1. *Assume in a model with labor search that the disaster risk is constant and the labor market is at its steady state. The log risk-free rate is given by*

$$\log R_f = -\log\beta + \frac{1}{\psi}\left(\mu + \frac{1}{2}\sigma_\epsilon^2\right) - \frac{1}{2}\left(\gamma + \frac{\gamma}{\psi}\right)\sigma_\epsilon^2 + \left(\frac{\frac{1}{\psi}-\gamma}{1-\gamma}\mathbb{E}\left[e^{(1-\gamma)\zeta}-1\right] - \mathbb{E}\left[e^{-\gamma\zeta}-1\right]\right)\tilde{\lambda}. \quad (2.28)$$

The riskfree rate is decreasing in $\tilde{\lambda}$.

The risk of a rare disaster increases agents' desire to save, which drives down the riskfree rate. In contrast to Theorem 2, this result holds regardless of the value of ψ.

Lemma 2. *Assume in a model with labor search that disaster risk is constant and the labor market is at its steady state. The equity premium is given by*

$$\log\left(\frac{\mathbb{E}_t[R_{t+1}]}{R_f}\right) = \gamma\sigma_\epsilon^2 + \tilde{\lambda}\mathbb{E}\left[\left(e^{-\gamma\zeta}-1\right)\left(1-e^{\zeta}\right)\right]. \quad (2.29)$$

The equity premium is increasing in $\tilde{\lambda}$.

The first term in the equity premium represents the normal-times risk in production. Given the low volatility in productivity and consumption, this first term will be very small in our calibrated model. The second term represents the effect of rare disasters. A rare disaster causes an increase in marginal utility, represented by the term $e^{-\gamma\zeta}-1$, at the same time as it causes a decrease in the value of the representative firm, as represented by $e^{\zeta}-1$. Because the representative firm declines in value at exactly the wrong time, its equity carries a risk premium. This also implies that the equity premium is unambiguously increasing in the probability of a disaster.

How are the risk premium and the riskfree rate connected to the effective time-discount factor and to firm valuations? We now answer this question. Consider a transformation of the price-dividend ratio:

$$h(\tilde{\lambda}) = -\log\left(1 + \frac{D_t}{P_t}\right). \quad (2.30)$$

Then $h(0)$ is the price-dividend ratio when there is no disaster risk:

$$h(0) = \log\beta + \left(1 - \frac{1}{\psi}\right)\left(\mu + \frac{1}{2}(1-\gamma)\sigma_\epsilon^2\right). \tag{2.31}$$

Note that in this iid economy where quantities are at their steady-state values, P_t/D_t is a constant that depends on $\tilde{\lambda}$. There is a tight connection between the price-dividend ratio and the effective time-discount factor.

Theorem 3. *Assume in a model with labor search that disaster risk is constant and the labor market is at its steady state. Define $\hat{\beta}(\tilde{\lambda})$ as in Theorem 2. Define $h(\tilde{\lambda})$ as in (2.30). Then*

$$h(\tilde{\lambda}) - h(0) = \log\hat{\beta}(\tilde{\lambda}) - \log\beta. \tag{2.32}$$

Thus the price-dividend ratio is decreasing in $\tilde{\lambda}$ if and only if $\psi > 1$.

Applying (2.28) and (2.29), we see that the effect of disaster risk on $h(\tilde{\lambda})$ can be decomposed into a discount rate effect (which in turn can be decomposed into a risk premium and riskfree rate effect) and an expected growth effect, as in Campbell and Shiller (1988):

$$\begin{aligned} h(\tilde{\lambda}) - h(0) = &-\underbrace{\left(\frac{\frac{1}{\psi}-\gamma}{1-\gamma}\left(\mathbb{E}\left[e^{(1-\gamma)\zeta}\right]-1\right) - \left(\mathbb{E}\left[e^{-\gamma\zeta}\right]-1\right)\right)\tilde{\lambda}}_{\text{risk-free rate effect}} \\ &+ \underbrace{\mathbb{E}\left[\left(e^{-\gamma\zeta}-1\right)\left(e^{\zeta}-1\right)\right]\tilde{\lambda}}_{\text{risk premium effect}} + \underbrace{\left(\mathbb{E}\left[e^{\zeta}\right]-1\right)\tilde{\lambda}}_{\text{expected cash-flow effect}}. \end{aligned} \tag{2.33}$$

The decomposition (2.33) provides additional intuition for the effect of changes in the disaster probability on the economy. On the one hand, an increase in the risk of a disaster drives down the riskfree rate. This will raise valuations, all else equal. However, it also increases the risk premium and lowers expected cash flows. When $\psi > 1$, the risk premium and cash flow effects dominate the riskfree rate effect and an increase in the disaster probability lowers valuations.

We now explicitly connect these results to the labor market. First, as suggested by the result in Section 2.3.2, the greater are valuations, the greater is labor market tightness (see Appendix A2.1 for a rigorous proof). Because an increase in the probability lowers valuations, it lowers labor market tightness, provided that the EIS is greater than 1.

Corollary 1. *Assume in a model with labor search that disaster risk is constant and the labor market is at its steady state.*

1. *The price-dividend ratio is increasing as a function of labor market tightness.*

2. *Labor market tightness is decreasing in the probability of a disaster if and only if $\psi > 1$.*

When firms are faced with a higher risk of an economy-wide disaster, they have an incentive to reduce hiring. This decreases equilibrium tightness θ to the point where firms are indifferent between hiring and not. Thus higher disaster risk results in higher unemployment, lower vacancies, and lower firm valuations.

The previous discussion separates the effects of the risk premium and the riskfree rate on the price-dividend ratio and hence on firm incentives. What about the discount rate overall? Hall (2015) conjectures that a model that produces higher discount rates in recessions can drive co-movement of unemployment and the stock market. The analysis in this section shows that it is not discount rates per se that matter, but the combination of discount rates and growth expectations (it is also not necessary for these to be related to recessions driven by lower current productivity). For higher discount rates to be associated with lower unemployment, EIS greater than 1 is a necessary but not sufficient condition:

Corollary 2. *Assume in a model with labor search that disaster risk is constant and the labor market is at its steady state. The expected return is increasing in $\tilde{\lambda}$ if and only if*

$$1 - \mathbb{E}\left[e^{\zeta}\right] < \frac{1 - \frac{1}{\psi}}{1 - \gamma}\left(1 - \mathbb{E}\left[e^{(1-\gamma)\zeta}\right]\right). \tag{2.34}$$

The analysis in this section sheds light on the tight link between the valuation mechanism and the labor market. As we will show in the next section, this mechanism is helpful in quantitatively explaining historical fluctuations in the labor market.

2.4. Quantitative Results

Below, we compare statistics in our model to those in the data. Section 2.4.1 describes the calibration of parameters for preferences, labor market variables, and productivity in normal times. Section 2.4.2 describes assumptions on the disaster distribution. Given these assumptions, Section 2.4.3 shows what happens to labor market, business cycle, and financial moments when a disaster occurs or when the disaster probability increases. We then simulate repeated samples of length 60 years from our model. Section 2.4.4 describes statistics of labor market moments in simulated data. Section 2.4.5 describes statistics for business cycle and financial moments. Section 2.4.6 makes use of alternative calibrations to highlight the main mechanisms behind our results.

2.4.1. Model Parameters

Table 2.1 describes model parameters for our benchmark calibration. Unless otherwise stated, parameters are given in monthly terms. Labor productivity in normal times is calibrated to the labor productivity process from the postwar data (see Appendix A2.4 for data description). This implies a monthly growth rate μ of 0.18% and standard deviation σ_ϵ of 0.47%. We calibrate the separation rate to 3.5% as estimated by Shimer (2005). We calibrate the Cobb-Douglas elasticity η to 0.35, consistent with empirical estimates in Petrongolo and Pissarides (2001) and Yashiv (2000). The parameter κ, corresponding to unit costs of vacancy openings normalized by labor productivity, is set to 0.5, the average of estimates from Hall and Milgrom (2008) and Hagedorn and Manovskii (2008).[14] For the bargaining power of workers (B) and the flow value of unemployment (b), we use values from Hall and Milgrom (2008); these are 0.5 and 0.76 respectively. We set the matching efficiency ξ to 0.365, targeting a model population value for unemployment equal to 10%.

[14] Hagedorn and Manovskii (2008) find a constant and a pro-cyclical component in vacancy costs. We specify vacancy costs proportional to productivity for simplicity.

We calibrate the tightness-insulation parameter ν to match wage dynamics in the data.[15] Table 2.2 shows the standard deviation and autocorrelation of wages in the data, as well as the elasticity of wages with respect to labor market tightness and productivity. Also shown is the elasticity of labor market tightness to productivity. The elasticity of wages to labor market tightness is low throughout the sample, while the elasticity of wages to labor productivity ranges from 0.67 in the full sample, to close to unity in the sample after 1985. We consider two versions of the model, one that insulates wages from labor market tightness (our benchmark specification), and one with no tightness insulation (the Nash bargaining solution). For each case, we simulate 10,000 sample paths of 60 years of data and report the median, and the 5th and 95th percentile of each statistic. Tightness insulation allows the model to match the standard deviation of wages to that of the data; without tightness insulation, wages are too volatile. Tightness insulation is also consistent with other aspects of the data: it implies wages with unit elasticity with respect to productivity, but near zero elasticity with respect to labor market tightness. Under the Nash-bargaining solution, however, wages are unrealistically elastic with respect to labor market tightness.

We assume the EIS ψ is equal to 2 and risk aversion γ is equal to 5.7. As is standard in production-based models with recursive utility, an EIS greater than one is necessary for the model to deliver qualitatively realistic predictions for stock prices (see Section 2.3.4). An important question is whether this level of the EIS is consistent with other aspects of the data. Using instrumental variable estimation of consumption growth on interest rates, Hall (1988) and Campbell (2003) estimate this parameter to be close to zero. However, as noted by Bansal and Yaron (2004), this parameter estimate may be biased in models with time-varying second (or higher-order) moments. To gauge the impact of the mis-specification, we repeat the instrumental-variable regressions of consumption growth on government bill rates in data simulated from our model.[16] We find a mean estimate of 0.15, consistent with

[15] Following Hagedorn and Manovskii (2008), we calculate wages by multiplying the labor share by productivity.

[16] The instruments are twice-lagged consumption growth, the government bill rate, and the log price-productivity ratio.

the data. Thus, despite the assumption of an EIS greater than 1, our model replicates the weak relation between contemporaneous consumption growth and interest rates.

2.4.2. Size Distribution and Probability of Disasters

The distribution for the disaster impact ζ_t is taken from historical data on GDP declines in 36 countries over the last century (Barro and Ursua (2008)). Following Barro and Ursua, we characterize a disaster by a 10% or higher cumulative decline in GDP. The resulting distribution for $1 - e^{\zeta}$ is shown in Figure 2.6. We assume that, if a disaster occurs, there is a 40% probability of default on government debt (Barro (2006)).

We approximate the dynamics of the disaster probability λ_t in (2.20) using a 12-state Markov chain. The nodes and corresponding stationary probabilities are given in Table 2.3. The stationary distribution of monthly probabilities is approximately lognormal with a mean of 0.20% and standard deviation 1.97%. In comparison, the 10% criterion for a disaster implies that the annual frequency of disasters in the data is 3.7%, indicating that our assumption on the disaster frequency is conservative. We choose the persistence and the volatility of the disaster probability process to match the autocorrelation and volatility of unemployment in U.S. data.

Table 2.4 describes properties of the disaster probability distribution. Because this distribution is not available in closed form, we simulate 10,000 sample paths of length 60 years. We find that 53% of these sample paths do not have a disaster; thus the post-war period was not unusual from the point of view of our model. Because the distribution for the disaster probability is highly skewed, the average λ_t is much lower in samples that, ex post, have no disasters than it is in population. Below, we report statistics from these simulated data for unemployment, vacancies, and business cycle and financial moments. Unless otherwise stated, the model statistics are computed from the no-disaster paths.

2.4.3. The effect of disasters and disaster probabilities

To highlight the implications of time-varying disaster probability, our model assumes a simplified view of the disaster itself. As described in Section 2.3.3, a disaster is a one-time, permanent drop in labor productivity. Because consumption, dividends and wages scale with productivity, these variables all fall by equal percentages in a disaster; if for example productivity drops by 15% in a disaster, they also drop by 15%. While this view of a disaster is stylized, results in the literature (e.g. Nakamura, Steinsson, Barro, and Ursua (2013) and Tsai and Wachter (2015)) suggest that introducing more complicated dynamics are unlikely to alter the implications for non-disaster states, which are the main focus of our analysis.

Figure 2.7 shows what happens to the labor market and to the business cycle in the months following an increase in the disaster probability. We assume an increase in the (monthly) probability from 0.05% to 0.32%, representing an approximately two-standard deviation increase along a typical no-disaster path. This increased probability of a disaster reduces the optimal employment level because, even though current productivity is unchanged, future productivity is more risky. Firms substantially reduce vacancies when the shock hits; vacancies then slowly rise to a new steady state which is lower than before. During this time, unemployment steadily rises as well. Vacancies and unemployment take about two years to converge to their new steady states. This two-standard deviation increase in the disaster probability leads to an approximately 6% decrease in employment and a 25% decrease in vacancies at the end of the two-year period. As Figure 2.7 shows, the increase in unemployment coincides with a decline in stock valuations.

While vacancies and unemployment respond substantially to an increase in disaster probability, consumption does not. In the very short term, an increase in the disaster probability slightly increases consumption because investment in hiring falls. In the longer term, consumption falls because the lower level of employment implies lower output.[17]

[17] Bloom (2009) solves a model in which time-varying uncertainty leads to lower consumption and output;

Figure 2.8 shows what happens to financial markets following a two-standard deviation increase in the disaster probability. Equity returns fall dramatically because of the sharp decline in stock prices described above. However, in the months following the increase, equity returns are slightly higher because of the greater risk premium needed to compensate investors for bearing the risk of a disaster. At the same time, the government bill rate falls because the greater degree of risk in the economy leads investors to want to save.

2.4.4. Labor Market Moments

Table 2.5 describes labor market moments in the model and in the U.S. data from 1951 to 2013. Panel A reports U.S. data on unemployment U, vacancies V, the vacancy-unemployment ratio V/U, labor productivity Z, and the price-productivity ratio P/Z. The labor market results replicate those reported by Shimer (2005) using more recent data. The vacancy-unemployment ratio has a quarterly volatility of 39%, twenty times higher than the volatility of labor productivity of 2%. The correlation between Z and V/U is 10%, whereas the correlation between P/Z and V/U is 47%, consistent with the findings in Section 2.2.[18] The correlation is lower in the pre-1985 sample, and higher in the post-1985 sample. These findings, together with the more detailed analysis in Section 2.2, motivate the mechanism in this paper.

Panel B of Table 2.5 reports the statistics calculated from sample paths simulated from the model. We simulate 10,000 sample paths of length 60 years. We report means from the 53% of simulations that contain no disaster. Our model is calibrated to match the volatility of unemployment. However, the model can also explain the volatility of vacancies, and the high volatility of the vacancy-unemployment ratio. The model also correctly generates a large negative correlation between vacancies and unemployment. Other possible mechanisms, such as shocks to the separation rate, generate a counterfactual positive correlation between V and U (Shimer (2005)). In addition, our model captures the low correlation between the

our model is consistent with the data he reports.

[18] As noted in Section 2.2, we follow Shimer (2005) in using a low-frequency HP filter with smoothing parameter 10^5. We report volatilities of log deviations from trend.

labor market and productivity and the relatively high correlation between the labor market and stock prices; it overstates the latter correlation because a single state variable drive both. However, a united mechanism for both stock market and labor market volatility is a better description of the data compared to models based on realized productivity, especially for the U.S. data from mid-1980s to the present.

Figure 2.9 shows the Beveridge curve (namely, the locus of vacancies and unemployment) in the data and in the model. The position of the economy along the historically downward sloping Beveridge curve is an important business cycle indicator (Blanchard, Diamond, Hall, and Yellen (1989)). The time-varying risk mechanism in our model is able to generate such negative correlation, and as a result, the model values are concentrated along a downward sloping line. In our model, an increase in risk and a decrease in expected growth leads to downward movement along the Beveridge curve. Following an increase in disaster probability, the economy converges to the new optimal level of employment which is lower than before. Because the matching function is increasing in both vacancies and unemployment, a lower level for vacancies is needed to maintain the employment level. The model is able to generate a wide range of values on the vacancy-unemployment locus, including data values at the lower right corner of the Beveridge curve observed during the Great Recession which correspond to high values for the disaster probability.

2.4.5. Business Cycle and Financial Moments

We now turn to the model's implications for consumption, output, and for financial market variables. Table 2.6 shows that the model produces a low volatility of consumption and output, just as in the data. The volatility for consumption (2.3%) is slightly lower than for output (2.5%), reflecting the consumption-smoothing motives of the agent.

There are two independent dimensions to cyclicality in the model, namely, comovement with labor productivity and with disaster risk. In the model, the effect of productivity shocks on consumption and output growth is identical. This is not the case for disaster risk, however. Consumption equals output by the firm, plus home production, minus investment in hiring. Because both output and investment are pro-cyclical with respect to disaster probability, the consumption response to disaster probability shocks is weaker than the output response, as shown in Figure 2.7. This creates a higher volatility in output growth compared to consumption growth, in line with the data.[19] The volatility of consumption and output is substantially higher in population than in samples without rare disasters, which are comparable to the post-war period.

Table 2.6 also shows that the model produces a realistically low average return and volatility for government bills; these are 3.6% and 3.8%. respectively. While somewhat higher than in the data postwar, these are very low compared with the values for equity returns (see below), and lower than in many models of production. The data fall well within the confidence bands implied by the model. Average returns on government bills are low in the model because of the precautionary savings motives arising from the risk of a disaster (Section 2.3.4).

Even though output can have long periods with small shocks, there remains the possibility of a large disaster. Because firms' cash flows are exposed to this disaster, in equilibrium, investors require a high premium to hold equity. Indeed, in samples without disasters generated from the model, the median equity premium is 6.7%. Because our model does not include financial leverage, we follow common practice (see, e.g. Nakamura, Steinsson, Barro, and Ursua (2013)) and report data values that are adjusted for leverage in the table.[20] The equity premium generated by our model is in fact higher than the adjusted value in the data, 5.3%, and is not far from the unadjusted value of 7.9%.[21]

Besides matching the equity premium, our model can also generate high levels of return

[19]Note that our definition of measured consumption does not include the flow value of unemployment as described in Section 2.3.3.4, and is therefore directly comparable to consumption expenditures in the data. Model-implied consumption volatility including the flow value of unemployment, $b_t(1-N_t)$, is 1.4%.

[20]Lemmon, Roberts, and Zender (2008) report an average market leverage ratio of 28% among U.S. firms from 1965 to 2003. Accordingly, the unlevered equity premium is calculated multiplying stock returns by 0.72.

[21]The population equity premium generated by the model is even higher: 13.3%. This higher value reflects the fact that samples that contain disasters have higher disaster probabilities, and hence higher risk premia. Because of the noise induced by disasters, this value is difficult to compare to any one historical sample.

volatility. We can see this already in Figure 2.8 from the large return response in the event of an increase in the disaster probability. Table 2.6 shows, indeed, that return volatility implied by the model is 19.8% per annum, above the unlevered value in the data and close to the unadjusted value of 17.6%. While iid models such as Barro (2009) and Gabaix (2011) can explain why there is an equity premium in the context of production, it is harder to explain why returns are volatile even in periods when no disasters take place.[22] In our model, return volatility comes about through time variation in the probability of the disaster. When this probability rises, future prospects for growth dim, and more importantly, the discount rate for this future growth increases. Embedded in the value of a firm is the value of a worker who is in place. When firm values fall, so too do the incentives for hiring. Thus our model produces high equity volatility, even though volatility of output is low.

A problem often faced by dynamic models with production is low riskiness of firm cash flows. Firms respond to bad news about future productivity (concerning its mean, its riskiness, or both) by cutting investment, and increasing dividends. This makes firm equity a hedge and decreases both the equity premium and return volatility. To produce reasonable values, models that focus on investment assume counterfactually high leverage (Gourio (2012)), or assume that stocks are something other than the dividend claim (Croce (2014)). Our model is also one of investment; posting a vacancy implies an investment in hiring. However, we are able to match the equity premium and return volatility without the use of leverage. One reason for this is the relative insensitivity of wages to labor market conditions. Another reason is that our model is one where unemployment and stock returns share an underlying process, and unemployment is highly volatile. We discuss these mechanisms further in the next section.

[22]In periods with disasters, returns will be volatile because cash flows are volatile. In our model, the population value for return volatility is 40% per annum.

2.4.6. Sources of Volatility and Risk Premia

We compare three alternative specifications to our benchmark model to highlight the sources of volatility and risk premia: a model with constant disaster probability, where disaster probability is set to 0.20%, the stationary mean in the benchmark model; a model with no disaster risk; and a model with Nash-bargained wages, namely, $\nu = 1$. In all cases, we follow the same simulation strategy as before, namely simulating 10,000 samples with length 60 years. We report results from samples without disasters, which is 53% of samples in the time-varying model and 24% in the constant disaster risk model.[23] When relevant, we also report population values.

Table 2.7 reports labor market volatility in the alternative specifications. If risk is not time-varying, labor market variables and P/Z are constant. This confirms that the only source of fluctuation in the labor market is disaster probability. The case without any disasters yields the same volatility as the case with constant disasters (recall that we are reporting results from no-disaster samples). The case without tightness insulation (but with time-varying risk) does produce some volatility in unemployment, vacancies, and in the vacancy-unemployment ratio, but much less than in our benchmark case. In this case, the risk of future productivity declines (as represented by low tightness) is passed on to workers in the form of lower wages. Thus firms maintain hiring when risk goes up, and unemployment as well as prices fluctuate much less than in the data. The resulting wage process also differs sharply from its empirical counterpart, as shown in Table 2.2.

Table 2.8 reports business cycle and financial moments. We first describe the volatility of consumption and output. In the absence of time-varying risk, consumption growth and output growth have the same volatility. Moreover, this volatility is lower as compared to our benchmark case with time-varying risk. Thus time-varying disaster risk causes some fluctuations in consumption and output due to firm's optimal investment decisions. Con-

[23]There are fewer disasters in the model with time-varying λ as opposed to constant λ because the process is highly skewed; most of the time λ takes on values consistent with few disasters.

stant λ and zero λ (no disaster risk) have the same implications for consumption and output in samples without disasters. Allowing for time-varying λ, but eliminating the tightness insulation from wages, has similar macroeconomic implications as setting λ to be a constant. Without tightness insulation, time-varying risk has only a small impact on firms' investment in hiring for the reasons described above: firms can pass greater risk of a disaster on to their employees in the form of lower wages. However, we do not see this in the data.

We now turn to the financial moments. The model without disaster risk delivers a negligible equity premium and equity volatility, as well as an unrealistically high riskfree rate. This is in spite of the fact that the model is not the benchmark real-business-cycle model; rather it still is a DMP model with tightness-insulation. The reason is that output and thus firm cash flows remain smooth in this model. The model with constant disaster risk has a high equity premium, however equity volatility is still negligible in periods without disasters.[24]

Interestingly, the case with time-varying λ and no tightness insulation has implications for equity returns that are dramatically different than the case with tightness insulation. In this case, investment in the firm becomes very safe because the firm has a cost structure that is highly sensitive to cyclical conditions in the economy. In times of low disaster probability, employment increases and wages increase substantially due to the high sensitivity of wages to labor market tightness. In contrast, when employment falls, wages adjust rapidly downward. Thus investment in the firm forms a hedge against the main risks in the economy, and, in equilibrium, risk premia are negative.

While these results point to the importance of tightness-insulation for wages, it is also the case that tightness-insulation alone does not lead to an equity premium, high stock return volatility, or for that matter, volatile unemployment, as illustrated by our case with

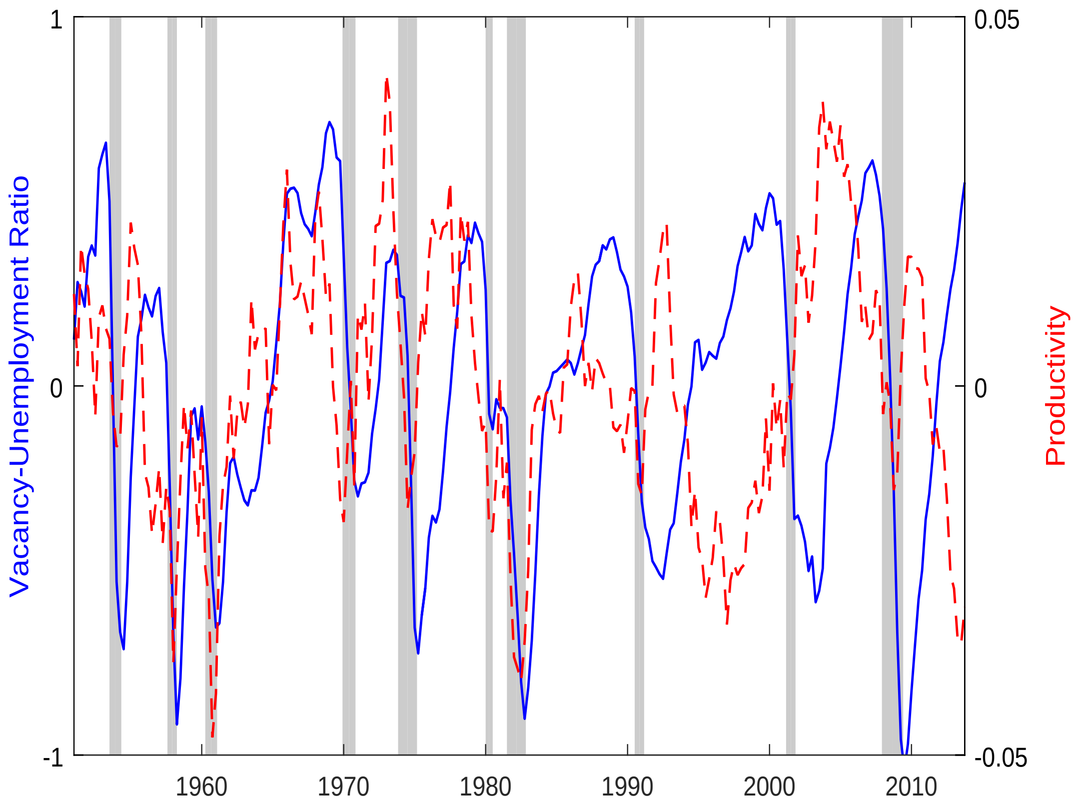
[24]In the model with constant λ, samples without disasters have higher average excess returns than in population; this is the effect of the Peso problem described in Jorion and Goetzmann (1999). In the model with time-varying λ, somewhat surprisingly, the opposite effect holds and the samples without disasters have lower average excess returns. The reason is that samples that, ex post, have no disasters are also those that, ex post, have lower disaster probabilities, and hence lower equity premia. The time-varying λ case has higher population risk premia for the reasons given in Wachter (2013).

constant disaster risk, or no disaster risk. In these cases, equity volatility is indeed higher than consumption and output volatility, but the difference is slight: 1.7% versus 1.3% per year. Unlike in models with wage rigidities (Uhlig (2007), Favilukis and Lin (2014)), or high operating leverage induced by high and stable wages (Petrosky-Nadeau, Zhang, and Kuehn (2013)), wages fluctuate fully in response to changes in productivity in our model; it is their response to labor market conditions that is dampened (see Table 2.2). It is time-varying risk premia arising from the risk of a disaster that generates equity volatility.

2.5. Conclusion

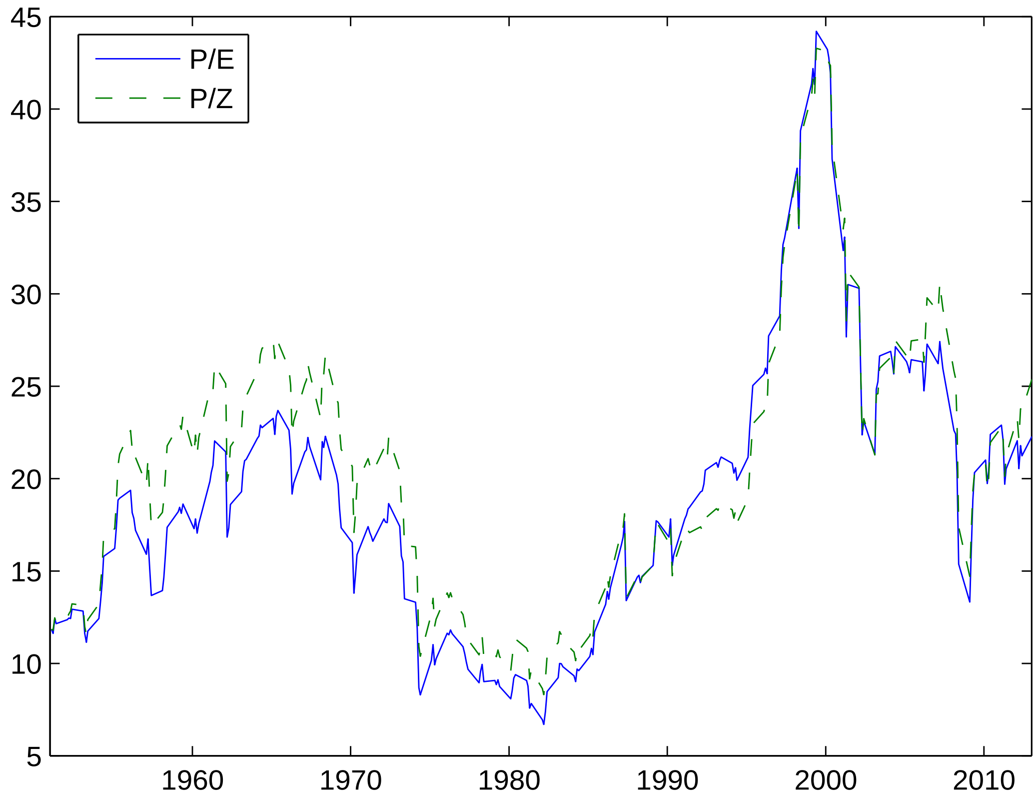
This paper shows that a business cycle model with search and matching frictions in the labor market and a small and time-varying risk of an economic disaster can simultaneously explain labor market volatility, stock market volatility and the relation between unemployment and stock market valuations. While tractable, the model can generate high volatility in labor market tightness along with realistic aggregate wage dynamics. The findings suggest that time variation in aggregate uncertainty offers an important channel, through which the DMP model of labor market search and matching can operate. The model provides a mechanism through which job creation incentives of firms and stock market valuations are tightly linked, as the comovement of labor market tightness and stock market valuations in the data suggest. While the presence of disaster risk and realistic wage dynamics generate a high unlevered equity premium, the source of labor market volatility and stock market volatility is time variation in risk. Finally, the model is consistent with basic business cycle moments such as consumption growth and output growth.

Figure 2.1: Vacancy-Unemployment Ratio and Labor Productivity: 1951 - 2013



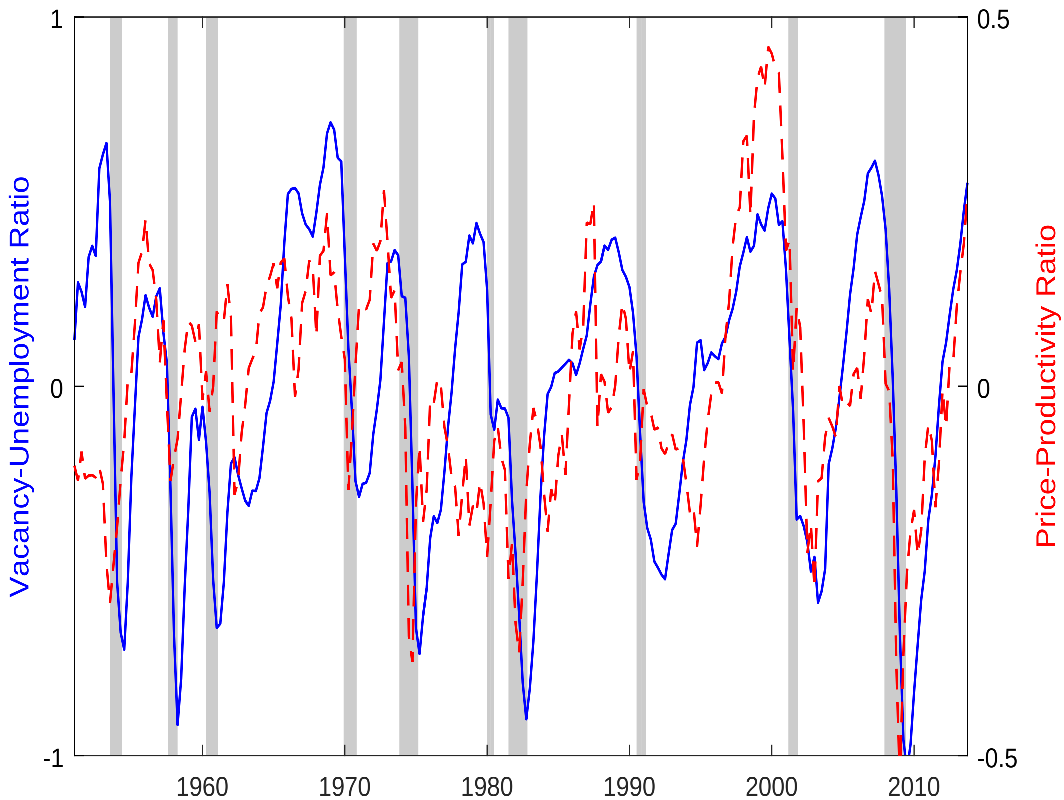
Notes: The solid line shows the vacancy-unemployment ratio, the dashed line labor productivity. Both variables are reported as log deviations from an HP trend with smoothing parameter 10^5. Shaded periods are NBER recessions.

Figure 2.2: Valuation Ratios: 1951 - 2013



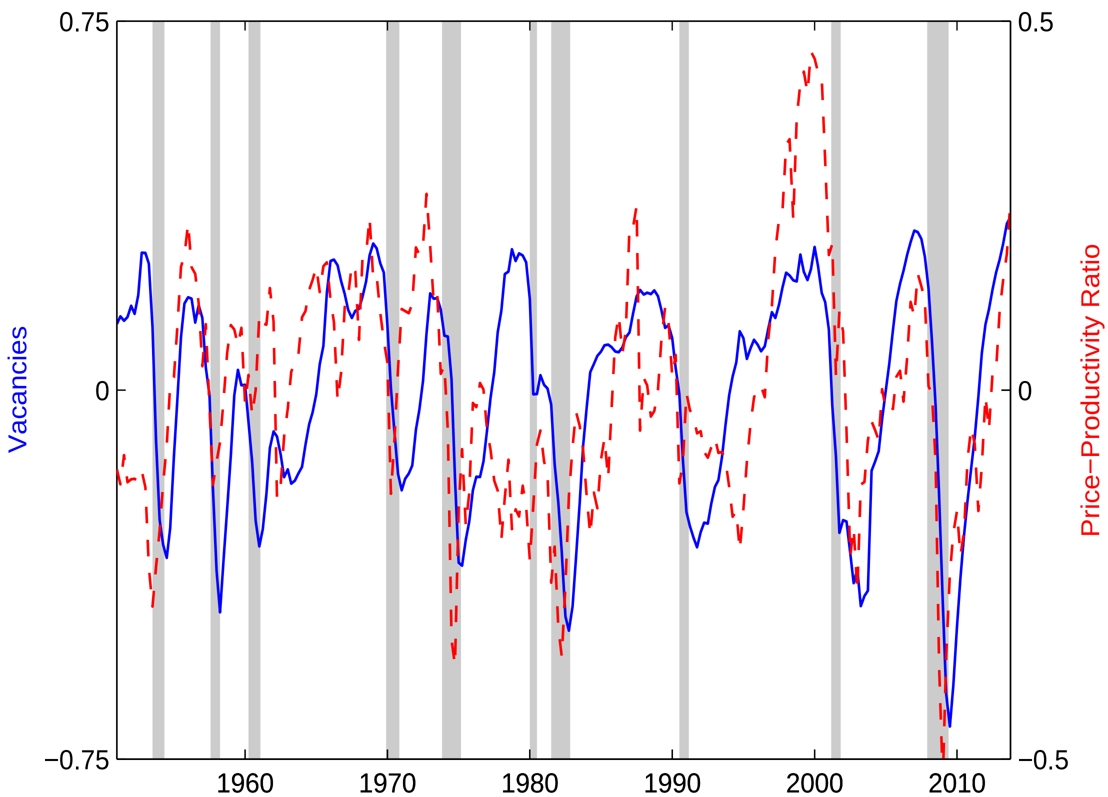
Notes: P/Z denotes the price-productivity ratio defined as the real price of the S&P composite stock price index P divided by labor productivity Z. P/E is the cyclically adjusted price-earnings ratio of the S&P composite stock price index. P/Z is scaled such that P/Z and P/E are equal in the first quarter of 1951.

Figure 2.3: Vacancy-Unemployment Ratio and Price-Productivity Ratio: 1951 - 2013



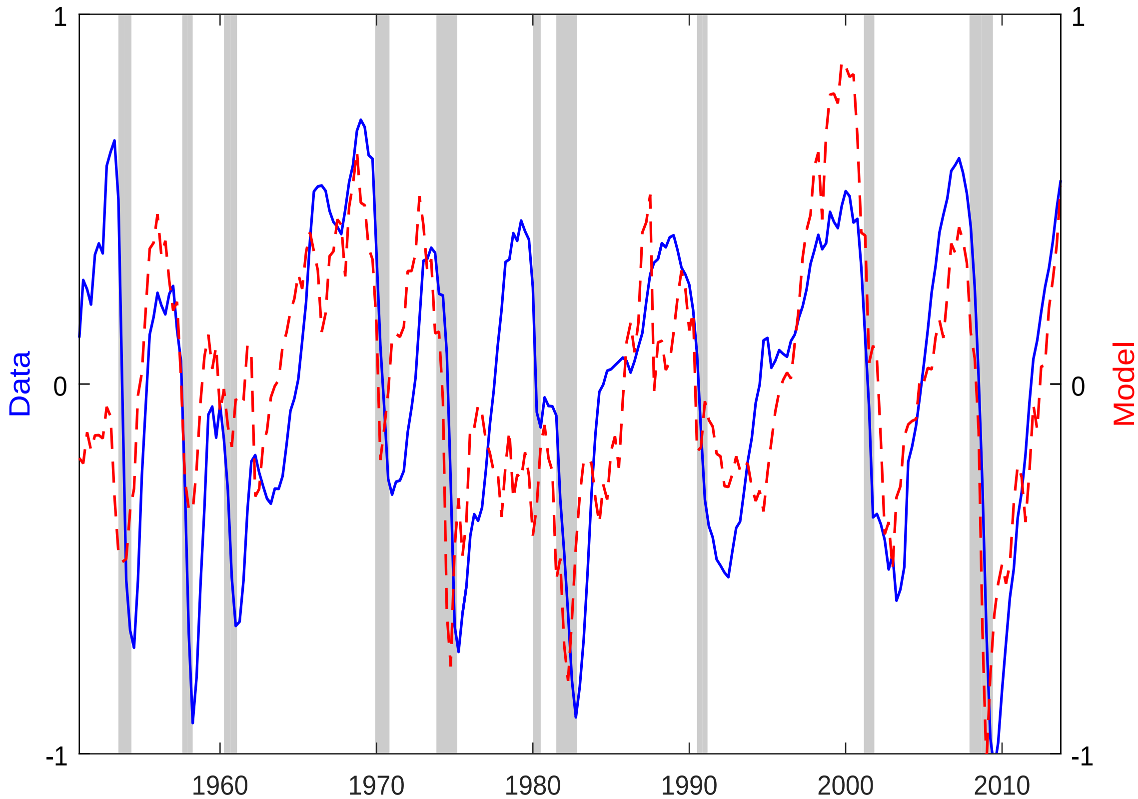
Notes: The solid line shows the vacancy-unemployment ratio, the dashed line the price-productivity ratio. Both variables are reported as log deviations from an HP trend with smoothing parameter 10^5. Shaded periods are NBER recessions.

Figure 2.4: Vacancy Openings and Price-Productivity Ratio: 1951 - 2013



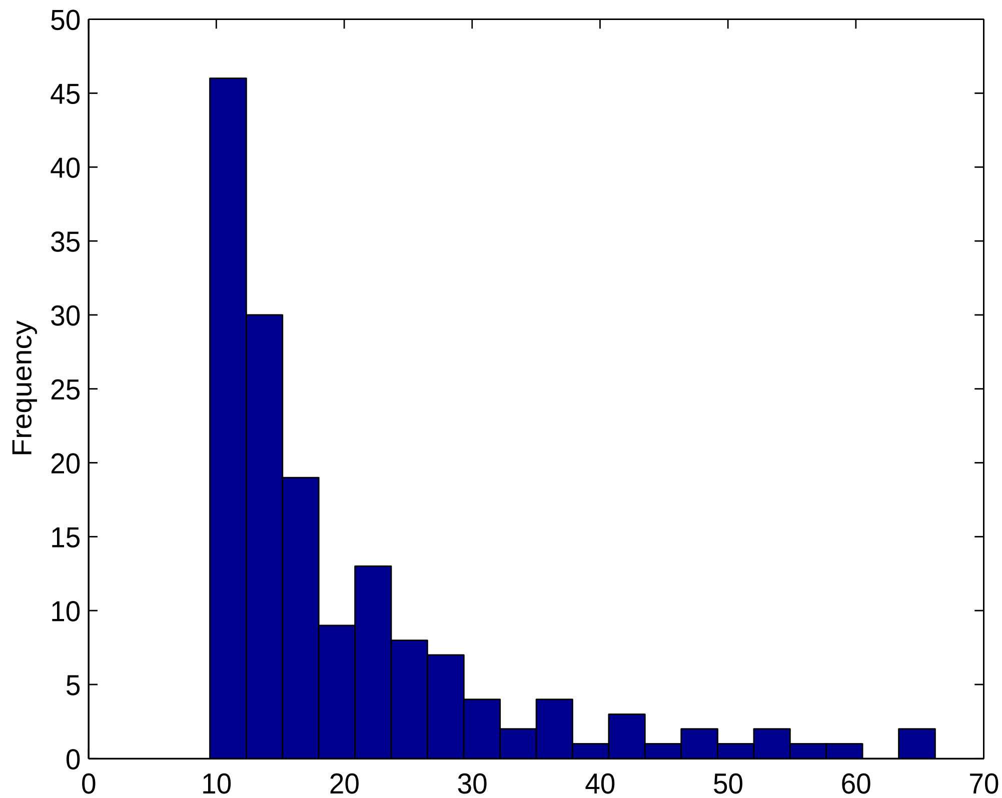
Notes: The solid line shows vacancies, the dashed line the price-productivity ratio. Both variables are reported as log deviations from an HP trend with smoothing parameter 10^5. Shaded periods are NBER recessions.

Figure 2.5: Vacancy-Unemployment Ratio: Data vs. Model



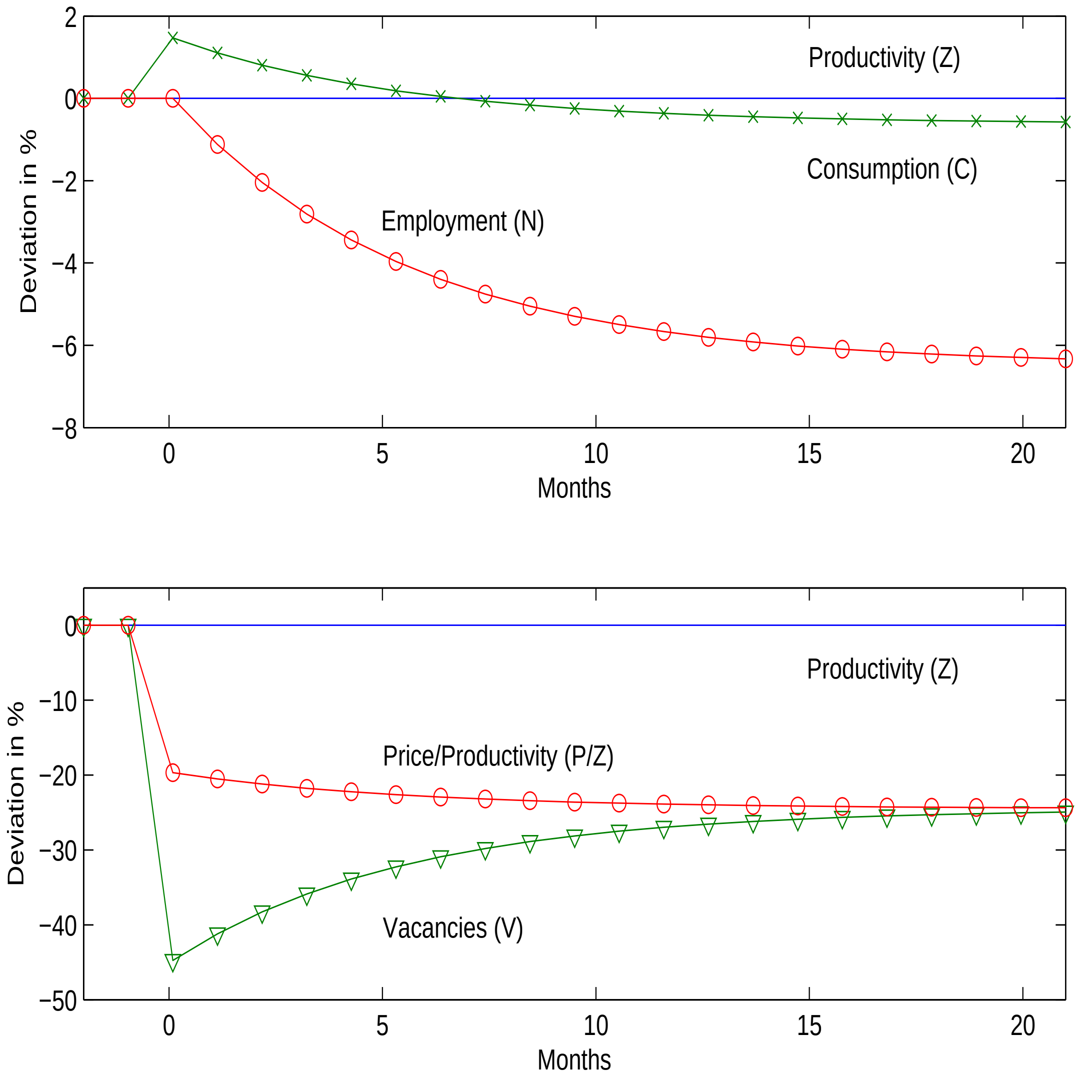
Notes: The solid line and the dashed line show the vacancy-unemployment ratio in the data and in the model, respectively. Model-implied vacancies are calculated by substituting the price-productivity ratio and employment level from the data into equation (2.12), assuming labor-market parameters given in Table 2.1. Values are log deviations from an HP trend with smoothing parameter 10^5. Shaded periods are NBER recessions.

Figure 2.6: Size Distribution of Disaster Realizations



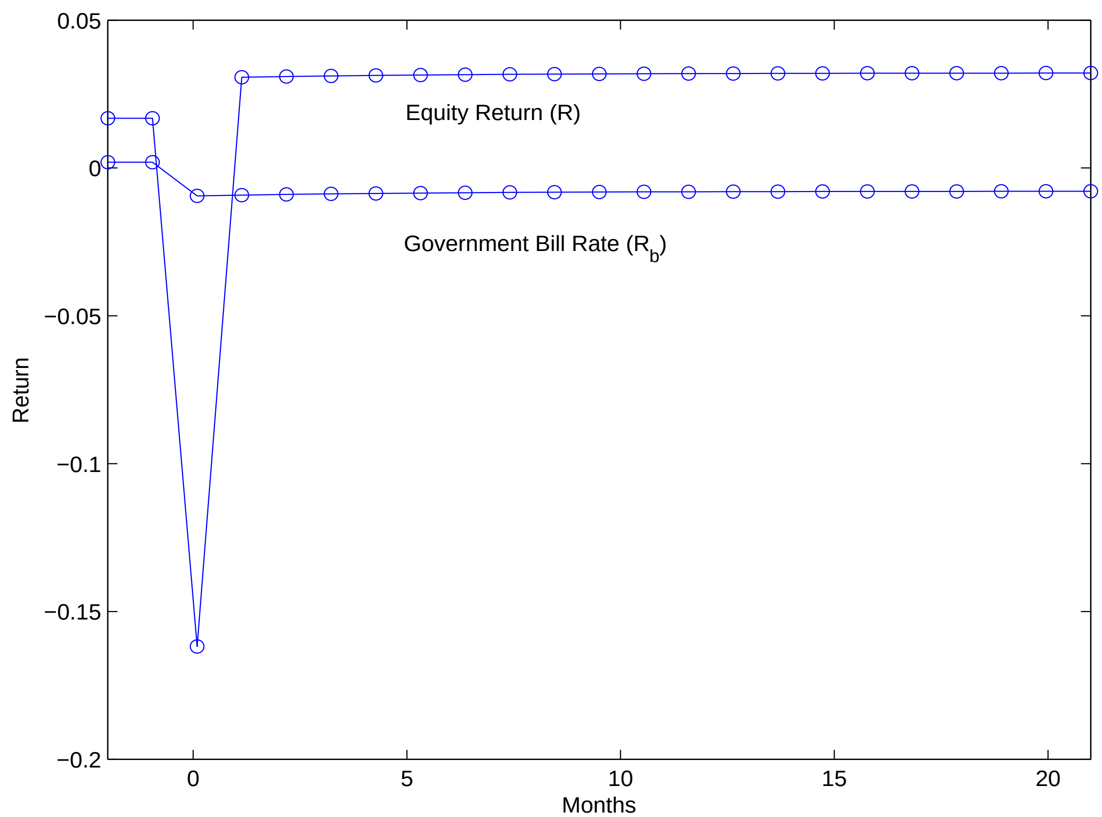
Notes: Histogram shows the distribution of large declines in GDP per capita (in percentages). Data are from Barro and Ursua (2008). Values correspond to $1 - e^{\zeta}$ in the model.

Figure 2.7: Macroeconomic Response to Increase in Disaster Probability



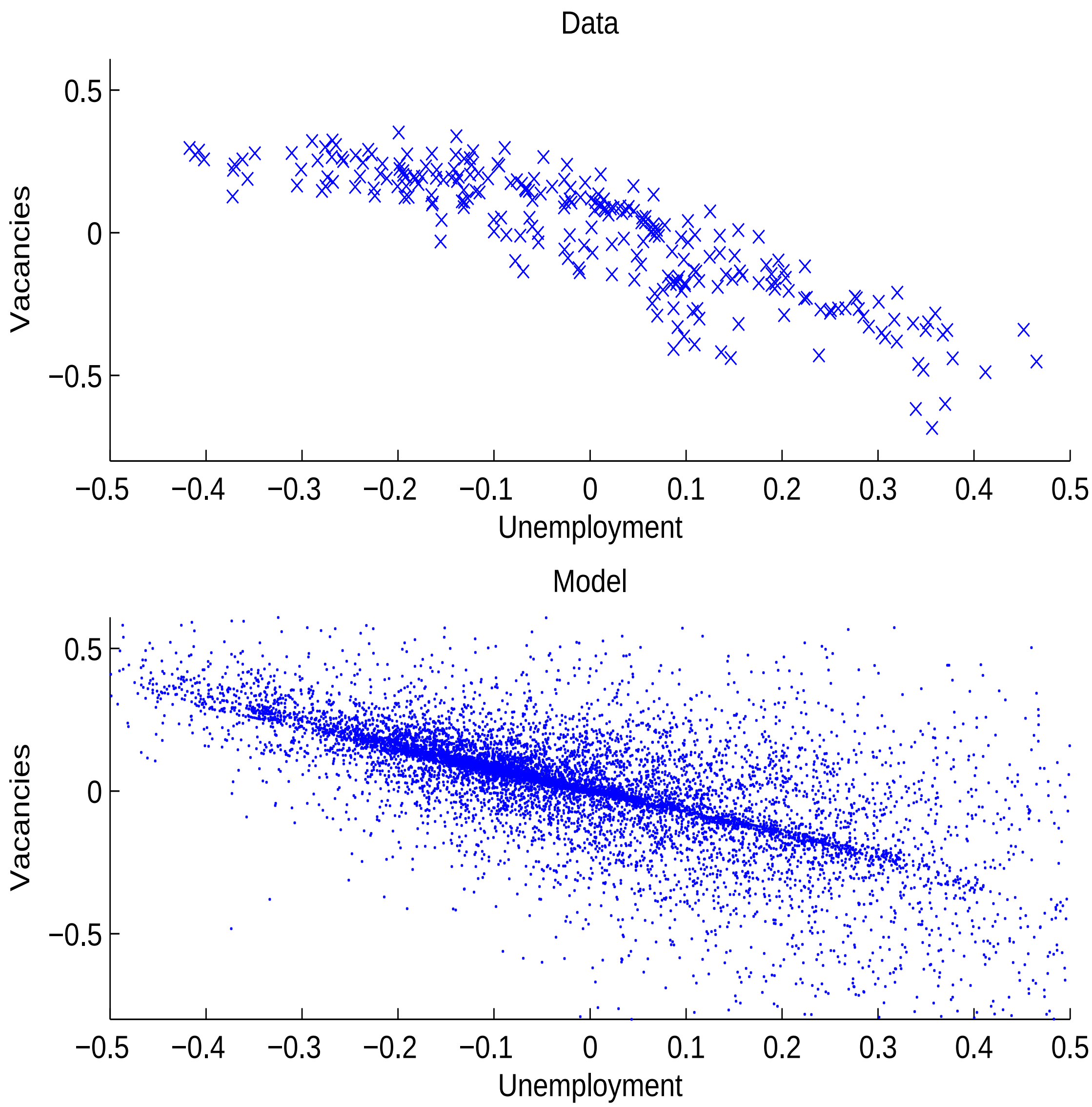
Notes: In month zero, monthly disaster probability increases from 0.05% to 0.32% and stays at 0.32% in the remaining months.

Figure 2.8: Return Response to Increase in Disaster Probability



Notes: In month zero, monthly disaster probability increases from 0.05% to 0.32% and stays there in the remaining months.

Figure 2.9: Beveridge Curve



Notes: Data are quarterly from 1951 to 2013. Model implied curve is a quarterly sample with length 10,000 years from the stationary distribution. All values are log deviations from an HP trend with smoothing parameter 10^5.

Table 2.1: Parameters Values for Monthly Benchmark Calibration

Parameter	Value
Time preference, β	0.997
Risk aversion, γ	5.7
Elasticity of intertemporal substitution, ψ	2
Disaster distribution (GDP), ζ	multinomial
Productivity growth, μ	0.0018
Productivity volatility, σ_ϵ	0.0047
Matching efficiency, ξ	0.365
Separation rate, s	0.035
Matching function parameter, η	0.35
Bargaining power, B	0.50
Value of non-market activity, b	0.76
Vacancy cost, κ	0.50
Tightness insulation, ν	0.05
Government default probability, q	0.40

Table 2.2: Properties of Aggregate Wages

	SD	AC	$\epsilon_{W,\theta}$	$\epsilon_{W,Z}$	$\epsilon_{\theta,Z}$
Panel A: Data					
1951 - 2013	1.77	0.91	0.00	0.67	2.46
	—	—	[0.33]	[5.43]	[0.76]
1951 - 1985	1.21	0.91	0.01	0.35	11.22
	—	—	[2.75]	[3.04]	[3.86]
1986 - 2013	2.29	0.91	-0.01	1.07	-8.49
	—	—	[-1.15]	[6.79]	[-2.37]
Panel B: Benchmark model					
50%	1.71	0.91	0.01	0.99	0.00
5%	1.33	0.87	-0.01	0.95	-6.39
95%	2.31	0.95	0.03	1.05	6.08
Panel C: No tightness insulation					
50%	2.26	0.89	0.13	1.00	0.04
5%	1.80	0.83	0.08	0.74	-1.95
95%	2.89	0.93	0.18	1.27	1.93

Notes: SD denotes standard deviation, AC quarterly autocorrelation. Z is labor productivity, θ labor market tightness. Data are from 1951 to 2013. All data and model moments are in quarterly terms. We simulate 10,000 samples with length 60 years at monthly frequency and report quantiles from 53% of simulations that include no disaster realization. $\epsilon_{x,y}$ is the elasticity of variable x to y, namely, the regression coefficient of log x on log y. Data t-statistics in brackets are based on Newey-West standard errors. All variables are used in logs as deviations from an HP trend with smoothing parameter 10^5.

Table 2.3: Monthly Disaster Probability

Value	Stationary Probability
1×10^{-7}	0.0005
7×10^{-7}	0.0054
4×10^{-6}	0.0269
3×10^{-5}	0.0806
0.0002	0.1611
0.0012	0.2256
0.0076	0.2256
0.0495	0.1611
0.3212	0.0806
2.0827	0.0269
13.5045	0.0054
87.5661	0.0005

Notes: Table lists the nodes of a 12-state Markov process which approximates an AR(1) process for log probabilities. Disaster probabilities are in percentage terms.

Table 2.4: Monthly Disaster Probability in Simulations

		No-Disaster				All Simulations			
	Population	Mean	5%	50%	95%	Mean	5%	50%	95%
$\mathbb{E}[\lambda]$	0.20	0.05	0.01	0.03	0.16	0.20	0.01	0.07	0.75
$\sigma(\lambda)$	1.97	0.20	0.01	0.11	0.58	0.84	0.02	0.27	2.81
$\rho(\lambda)$	0.91	0.86	0.65	0.89	0.96	0.87	0.66	0.90	0.96

Notes: σ denotes volatility, ρ monthly autocorrelation. Disaster probabilities are in percentage terms. Population is a sample of 100,000 years. We simulate 10,000 samples with length 60 years at monthly frequency and report statistics from all simulations as well as from 53% of simulations that include no disaster realization. All simulations are in monthly frequency.

Table 2.5: Labor Market Moments

	U	V	V/U	Z	P/Z	
Panel A: Data						
SD	0.19	0.21	0.39	0.02	0.16	
AC	0.94	0.94	0.95	0.88	0.89	
	1	-0.86	-0.96	-0.18	-0.44	U
	—	1	0.97	0.03	0.47	V
	—	—	1	0.10	0.47	V/U
	—	—	—	1	0.00	Z
	—	—	—	—	1	P/Z
Panel B: No-Disaster Simulations						
SD	0.17	0.19	0.33	0.02	0.14	
	(0.04)	(0.05)	(0.07)	(0.01)	(0.03)	
AC	0.95	0.76	0.90	0.93	0.91	
	(0.01)	(0.04)	(0.02)	(0.03)	(0.02)	
	1	-0.68	-0.90	-0.06	-0.92	U
	—	1	0.93	-0.06	0.90	V
	—	—	1	0.00	0.99	V/U
	—	—	—	1	0.01	Z
	—	—	—	—	1	P/Z
Panel C: Population						
SD	0.19	0.22	0.39	0.04	0.17	
AC	0.95	0.76	0.90	0.93	0.91	
	1	-0.69	-0.91	-0.06	-0.92	U
	—	1	0.93	-0.06	0.90	V
	—	—	1	0.00	0.99	V/U
	—	—	—	1	0.01	Z
	—	—	—	—	1	P/Z

Notes: SD denotes standard deviation, AC quarterly autocorrelation. Data are from 1951 to 2013. All data and model moments are in quarterly terms. U is unemployment, V vacancies, Z labor productivity and P/Z price-productivity ratio. We simulate 10,000 samples with length 60 years at monthly frequency and report means from 53% of simulations that include no disaster realization in Panel B. Standard errors across simulations are reported in parentheses. Population values in Panel C are from a path with length 100,000 years at monthly frequency. Standard deviations, autocorrelations and the correlation matrix are calculated using log deviations from an HP trend with smoothing parameter 10^5.

Table 2.6: Business Cycle and Financial Moments

	$\mathbb{E}[\Delta c]$	$\mathbb{E}[\Delta y]$	$\sigma(\Delta c)$	$\sigma(\Delta y)$	$\mathbb{E}[R - R_b]$	$\mathbb{E}[R_b]$	$\sigma(R)$	$\sigma(R_b)$
Data	1.97	1.90	1.78	2.29	5.32	1.01	12.26	2.22
Simulation 50%	2.16	2.16	2.28	2.47	6.66	3.64	19.78	3.83
Simulation 5%	1.80	1.79	1.59	1.71	-0.02	0.06	11.75	0.87
Simulation 95%	2.51	2.54	3.44	3.72	20.39	4.96	33.94	12.50
Population	1.63	1.63	6.85	6.89	13.32	1.22	38.97	12.19

Notes: The table reports means and volatilities of log consumption growth (Δc), log output growth (Δy), the government bill rate (R_b) and the unlevered equity return R in historical data and in data simulated from the model. All data and model moments are in annual terms. Historical data are from 1951-2013. We simulate 10,000 samples with length 60 years from the model and report quantiles from 53% of simulations that include no disaster realization. Population values are from a path with length 100,000 years. In the data, net equity returns are multiplied by 0.72 to adjust for leverage. Raw equity returns in the data have a premium of 7.90% and volatility of 17.55% over this period.

Table 2.7: Comparative Statics for Labor Market Volatility

	U	V	V/U	Z	P/Z
Data	0.19	0.21	0.39	0.02	0.16
Benchmark	0.17	0.19	0.33	0.02	0.14
Constant λ	0.00	0.00	0.00	0.02	0.00
No disaster	0.00	0.00	0.00	0.02	0.00
No tightness insulation	0.06	0.06	0.11	0.02	0.05

Notes: Standard deviations (in log deviations from an HP trend) for unemployment (U), vacancies (V), labor productivity (Z) and the price-productivity ratio (P/Z) in the data and in four versions of the model. Data are from 1951 to 2013. All data and model moments are in quarterly terms. Model values are calculated by simulating 10,000 samples with length 60 years at a monthly frequency. We report means from simulations that include no disaster realizations. In the constant disaster probability model, we set disaster probability to 0.20%, the stationary mean.

Table 2.8: Comparative Statics for Business Cycle and Financial Moments

	$\mathbb{E}[\Delta c]$	$\mathbb{E}[\Delta y]$	$\sigma(\Delta c)$	$\sigma(\Delta y)$	$\mathbb{E}[R - R_b]$	$\mathbb{E}[R_b]$	$\sigma(R)$	$\sigma(R_b)$
Data	1.97	1.90	1.78	2.29	5.32	1.01	12.26	2.22
Panel A: Benchmark								
50%	2.16	2.16	2.28	2.47	6.66	3.64	19.78	3.83
Population	1.63	1.63	6.85	6.89	13.32	1.22	38.97	12.19
Panel B: Constant λ								
50%	2.16	2.16	1.31	1.31	10.27	-3.48	1.73	0.00
Population	1.59	1.59	4.03	4.03	9.94	-3.66	3.49	2.16
Panel C: No Disaster Risk								
50%	2.16	2.16	1.32	1.32	0.16	5.12	1.70	0.00
Population	2.16	2.16	1.32	1.32	0.16	5.12	1.71	0.00
Panel D: No Tightness Insulation								
50%	2.16	2.16	1.47	1.52	-49.63	3.67	11.55	3.32
Population	1.68	1.68	6.46	6.44	-47.76	1.53	20.32	11.27

Notes: Δc denotes log consumption growth, Δy log output growth, R the unlevered equity return, R_b the government bill rate. All data and model moments are in annual terms. We simulate 10,000 samples with length 60 years at monthly frequency and report the median from samples that contain no disasters. In the constant disaster probability model, we set disaster probability to 0.20%, the stationary mean of the disaster probability process used in the benchmark model. Population values are from a path with length 100,000 years. Returns and growth rates are aggregated to annual values.

APPENDIX

A1. Appendix for Chapter 1

A1.1. Data

This section describes data items that are used in the paper, and not described elsewhere in the text. The book-to-market ratio (B/M) is the ratio of book equity to market equity. Book equity is defined as total stockholders' equity plus deferred taxes and investment tax credit minus the book value of preferred stock from Compustat. Market equity is the number of shares outstanding multiplied by the share price from CRSP. Total employment of an industry is the sum of number of employees reported in Compustat. Employment growth (H/N) is the annual growth rate of total employment. I compare total employment growth numbers from Compustat to those from KLEMS and obtain similar results. Investment rate (I/K) is the ratio of capital expenditures to property, plant, and equipment from Compustat. Profitability (π/A) is the ratio of earnings before interest and taxes to total assets. Size is defined as the market equity value. The FF-3, FF-5, UMD factors and 49 industry returns are downloaded from Kenneth French's website. The q-factors are computed following Hou, Xue, and Zhang (2014). Wage data by demographic groups comes from the U.S. labor files of the KLEMS dataset. Returns differentials based on the gross hiring rate are computed following Belo, Lin, and Bazdresch (2014). The IST level of an industry is computed as the inverse of the relative price of capital services. Industry-level price indices for capital services are taken from the main U.S. files of the KLEMS data set. Investment for equipment, software, and R&D is computed as the some of investment in equipment and intellectual property products from industry-level NIPA accounts. For the labor share of a firm (Wages/Output), the ratio of wages to output of the corresponding industry from KLEMS is used. Industry level TFP data are from KLEMS as well. Age groups available in KLEMS are treated as equally-distributed when a cutoff does not lie at the available age cutoffs in the KLEMS data.

A1.2. Level versus change in demographic composition

This section provides evidence that the "level" of the demographic composition is backward looking, while the "change" is forward looking. Table 1.24 shows that the level of the young-to-old ratio in the skilled workforce has no (or, negative, if anything) predictive power for future investment, while Table 1.25 presents evidence that past investment activity predicts current levels of the young-to-old ratio, but not changes. This is consistent with the idea that young-hiring is concentrated at times when high investment is expected. Therefore, industries that have had high investment over the last three years have increased the share of young employees in the skilled workforce. Industries that plan to increase investments with high embodied productivity move toward a younger workforce. Therefore, changes in the demographic composition contain information about future investment activity that has not realized yet, and indicate ex-ante exposure to risks associated with these investments.

A1.3. Wage dynamics around demographic shifts

Is there any cross-sectional variation in wage growth across young and old hiring portfolios? Is young-hiring a cost-cutting measure? This section provides some descriptive statistics on wages before and after the demographic shifts observed at the time of portfolio formation. Table 1.27 reports wage growth per employee and total wage growth for industries that are in the portfolios Y, M, and O. Portfolios are formed at time t. Industries do not differ significantly in wage growth per employee in the two years before portfolio formation, both for young and old employees. There is a dispersion in the portfolio formation year, where industries in portfolio Y have an average wage growth of 1.92% while it is 0.33% for industries in the old portfolio. This difference can be driven by the firms' desire to attract employees, and shrinks over the next three years after portfolio formation. Industries in portfolio O also experience high wage growth for old employees, on average, although their demand for old employees is high. This may be because the reduction in the number of old employees is driven by low-wage workers. The total wage bill growth of industries are also quite similar except for the portfolio formation year t. The high growth in the wage bill for young employees can be explained by the increase in their quantity, as the wage per employee effect is not very strong. Table 1.28 further shows that industries are very similar in terms of their wage cost share, labor share, and operating leverage during, before, and after portfolio formation.[1] This suggests that a focus of hiring activity on the young is not merely a cost measure that firms take.

A1.4. Cash-flow predictability

The argument developed in this paper is that, at the time the dispersion in demographic shifts is observed, future investment plans are priced in the stock market, and the risk premium associated with risks in future investment gives rise to a cross-sectional dispersion in expected returns. Bansal, Dittmar, and Lundblad (2005) show that value and momentum can be tracked down to cash-flow betas. I investigate the sensitivity of future portfolio cash-flows to aggregate TFP and IST shocks. Tables 1.32 and 1.33 show that 1-year and, especially, 3-year dividend growth of firms in portfolio Y have significantly higher positive exposure to IST shocks. This is consistent with the empirical results based on portfolio returns: differences in the future cash-flow performance of young and old hiring industries are well predicted by past realizations of past productivity shocks in new vintages of capital. This supports that young-hiring portfolio rely heavily on the productivity embodied in new capital. If new capital turns out more productive, these industries can build more productive capital per unit investment expenditure, and this is reflected in future cash-flows.

The cash-flow exposure results also shed light on the fundamental relation between the young-old hiring spread, value-growth, and industry momentum. Future cash-flows of winner industries are also more exposed to IST shocks, while value firm cash-flows are more exposed to TFP shocks. This is consistent with the comovement of these three returns, and their comovement with aggregate shocks discussed in Section 1.2.5.1.

[1] I also computed the distribution of wage cost indicators, and their average 5% and 95% values are very close, and are not reported for brevity.

A1.5. Vintage capital and IST

This section shows an isomorphism between the baseline model with investment-specific technology and a model with vintage capital. Let k_τ^v be the quantity of capital installed at time τ (or, analogously, investment at τ) and z_τ be the productivity of the vintage where z_τ is set at τ and does not change. Assuming that capital depreciates at rate δ, the effectively available capital at time t from capital installed at τ is given by

$$z_\tau(1-\delta)^{t-(\tau+1)}k_\tau^v, \tag{A.1}$$

where $t > \tau$. The total effective capital available to the firm is then given by

$$k_t = \sum_{\tau=-\infty}^{t-1} z_\tau(1-\delta)^{t-(\tau+1)}k_\tau^v, \tag{A.2}$$

which represents the remaining quantity from all past vintages of capital, after accounting for depreciation, multiplied by the vintage-specific productivity. As a result, the law of motion for effective capital is given by

$$k_{t+1} = (1-\delta)k_t + z_t k_\tau^v. \tag{A.3}$$

Because k_τ^v is equivalent to investment, the laws of motion in (1.3) and (A.3) are identical. Assuming that effective capital, k_t, enters the production in the same way as in (1.1), the model with IST entering capital accumulation directly, and the model with vintage-specific productivity are isomorphic.

A1.6. Unskilled labor

This section extends the baseline model to include unskilled labor in production. The production function in this case is given by

$$\tilde{y}_t = u_t a_t k_t^{\alpha_k} n_t^{\alpha_n} n_{u,t}^{\alpha_u}, \tag{A.4}$$

where the inputs are defined as in (1.1), n_t is skilled labor, and $n_{u,t}$ is unskilled labor input. $n_{u,t}$ is given by $e_u l_t^u$ where e_u denotes the efficiency units of an unskilled employee, and l_t^u is the quantity of unskilled labor. I assume that unskilled labor is freely adjustable every period. Therefore, the choice of the quantity of unskilled labor is a static problem. Let w_t^u denote the wage rate of an unskilled employee. The static problem of the is then given by

$$\max_{l_t^u} u_t a_t k_t^{\alpha_k} n_t^{\alpha_n} n_{u,t}^{\alpha_u} - w_t^u l_t^u. \tag{A.5}$$

The first order condition of this problem implies that α_u is the share of output that is paid to unskilled employees as wage: $\alpha_u \tilde{y}_t = w_t^u l_t^u$. As a result, the maximand of (A.5) is $(1-\alpha_u)\tilde{y}_t$. Because k_t and n_t are determined in period $t-1$, the optimal quantity of unskilled labor can be computed as $n_{u,t} = \left(\frac{\alpha_u \bar{y}_t}{w_t^u}\right)^{\frac{1}{1-\alpha_u}}$ where $\bar{y}_t = u_t a_t k_t^{\alpha_k} n_t^{\alpha_n} e_u^{\alpha_u}$. I specify the wage rate for unskilled employees as $w_t^u = \bar{w}^u \exp(\tau_a^u \, \Delta \log(a_t))$. I set the additional parameters to $e_u = 0.5$, $\bar{w}^u = 0.015 e_u$, $\tau_a^u = 1$, $\alpha_u = 0.23$, and set $\alpha_n = 0.23$ to account for the addition of another component for labor. I keep the remaining model assumptions and parameters values same as in the baseline case. Table 1.21 reports the results.

A1.7. Computation

In the model, output y_t, components of labor l_{t+1}^y and l_{t+1}^o, investment i, adjustment costs Φ_t^T, dividends d_t, and firm value p_t follow at the same rate at the balanced growth rate. Let $\tilde{a}_t$ denote the trend variable characterizing the growth path such that the variables above are stationary when normalized by $\tilde{a}_t$, where $\tilde{a}_t = a_t^{\frac{1}{1-\alpha_k-\alpha_n}} (z_t^a)^{\frac{\alpha_k}{1-\alpha_k-\alpha_n}}$. Capital grows at a higher rate due to investment-specific technological progress where the replacement cost of capital k_{t+1}/z_t follows the same growth path as the variables listed above. I solve the firm's maximization problem using value function iteration. I discretize the state space for capital, young and old labor on a grid with non-binding lower and upper bounds. I discretize the aggregate TFP and IST shocks using Gaussian-Hermite quadrature. The firm-specific productivity processes are discretized using the method of Rouwenhorst (1995). I use cubic spline interpolation between grid points to obtain the optimal policies.

A2. Appendix for Chapter 2

A2.1. Proofs of results for a general stochastic discount factor

The results in this section do not depend on our assumptions on M_{t+1} or Z_{t+1}.

Proof of Theorem 1 The representative firm pays out as dividend what is left from output after subtracting wage costs and investment in hiring:

$$D_t = Z_t N_t - W_t N_t - \kappa_t V_t. \tag{A.6}$$

The firm takes wages W_t and labor market tightness θ_t as given and maximizes the cum-dividend value

$$P_t^c = \max_{\{V_{t+\tau}, N_{t+\tau+1}\}_{\tau=0}^{\infty}} \mathbb{E}_t \sum_{\tau=0}^{\infty} M_{t+\tau} \left[Z_{t+\tau} N_{t+\tau} - W_{t+\tau} N_{t+\tau} - \kappa_{t+\tau} V_{t+\tau} \right], \tag{A.7}$$

subject to the law of motion for employment

$$N_{t+1} = (1-s) N_t + q(\theta_t) V_t. \tag{A.8}$$

The first order conditions with respect to V_t and N_{t+1} are given by

$$0 = -1 + l_t \frac{q(\theta_t)}{\kappa_t} \tag{A.9}$$

$$l_t = \mathbb{E}_t \left[M_{t+1} (Z_{t+1} - W_{t+1} + l_{t+1}(1-s)) \right], \tag{A.10}$$

where l_t is the Lagrange multiplier on the aggregate law of motion for employment level. Note that (A.10) can be interpreted as an Euler equation with l_t as the value of a worker inside the firm.

We expand (A.7), adding to each term in the summation an expression that, by (A.8), is equal to zero:

$$
\begin{aligned}
P_t^c &= Z_t N_t - W_t N_t - \kappa_t V_t - l_t \left(N_{t+1} - (1-s)N_t - \frac{q(\theta_t)}{\kappa_t}\kappa_t V_t \right) \\
&+ \mathbb{E}_t \left[M_{t+1} \left[Z_{t+1}N_{t+1} - W_{t+1}N_{t+1} - \kappa_{t+1}V_{t+1} - l_{t+1} \left(N_{t+2} - (1-s)N_{t+1} - \frac{q(\theta_{t+1})}{\kappa_{t+1}}\kappa_{t+1}V_{t+1} \right) \right] \right] \\
&+ ...
\end{aligned}
\tag{A.11}
$$

The terms $-\kappa_t V_t$ and $l_t \frac{q(\theta_t)}{\kappa_t} \kappa_t V_t$ cancel out for all t as a result of (A.9). Furthermore, $l_t N_{t+1}$ cancels out with $\mathbb{E}_t \left[Z_{t+1}N_{t+1} - W_{t+1}N_{t+1} + l_{t+1}(1-s)N_{t+1} \right]$ for all t as a result of (A.10). It follows that

$$P_t^c = Z_t N_t - W_t N_t + l_t(1-s)N_t. \tag{A.12}$$

Consider the ex-dividend value of equity $P_t = P_t^c - D_t$. Equation A.12 and the definition of dividends implies

$$
\begin{aligned}
P_t &= Z_t N_t - W_t N_t + l_t(1-s)N_t - Z_t N_t + W_t N_t + \kappa_t V_t \\
&= \kappa_t V_t + l_t(1-s)N_t \\
&= \frac{\kappa_t}{q(\theta_t)}(N_{t+1} - (1-s)N_t) + \frac{\kappa_t}{q(\theta_t)}(1-s)N_t \\
&= l_t N_{t+1}.
\end{aligned}
\tag{A.13}
$$

Combining (A.13) with (A.9) results in (2.10).

We now show (2.11). From (2.10) and the definition of dividends, it follows that

$$\begin{aligned}
R_{t+1} &\equiv \frac{P_{t+1}+D_{t+1}}{P_t} \\
&= \frac{l_{t+1}N_{t+2}+Z_{t+1}N_{t+1}-W_{t+1}N_{t+1}-\kappa_{t+1}V_{t+1}}{l_tN_{t+1}} \\
&= \frac{l_{t+1}\frac{N_{t+2}}{N_{t+1}}+Z_{t+1}-W_{t+1}-\frac{\kappa_{t+1}V_{t+1}}{N_{t+1}}}{l_t} \\
&= \frac{l_{t+1}\left[1-s+\frac{q(\theta_{t+1})}{\kappa t+1}\frac{\kappa_{t+1}V_{t+1}}{N_{t+1}}\right]+Z_{t+1}-W_{t+1}-\frac{\kappa_{t+1}V_{t+1}}{N_{t+1}}}{l_t} \\
&= \frac{Z_{t+1}-W_{t+1}+l_{t+1}(1-s)}{l_t} \\
&= \frac{Z_{t+1}-W_{t+1}+(1-s)\frac{\kappa_{t+1}}{q(\theta_{t+1})}}{\frac{\kappa_t}{q(\theta_t)}}
\end{aligned} \tag{A.14}$$

Using this result, we provide characterizations of returns and prices that will be useful in what follows.

Lemma 3. *Under the assumptions $\kappa_t = Z_t\kappa$ and $b_t = Z_tb$, the equity return equals*

$$R_{t+1} = \frac{(1-s)\frac{\kappa}{q(\theta_{t+1})}+1-w(\theta_{t+1})}{\frac{\kappa}{q(\theta_t)}}\frac{Z_{t+1}}{Z_t}, \tag{A.15}$$

where $w(\theta_t)$ is the wage normalized by productivity:

$$w(\theta_t) = (1-B)b + B(1+\kappa(\nu\theta_t+(1-\nu)\bar{\theta})). \tag{A.16}$$

The result follows directly from Theorem 1, Equation 2.11.

Given l_t as the value of a worker inside the firm, the Euler equation (A.10) suggests a notion of a payout of a worker inside the firm:

$$D_t^l = Z_t - W_t - sl_t. \tag{A.17}$$

Lemma 4. *Under the assumptions $\kappa_t = Z_t\kappa$ and $b_t = Z_tb$, the payout ratio of a worker* *employed in a firm is given by*

$$\frac{D_t^l}{l_t} = \frac{Z_t - W_t - sl_t}{l_t} \tag{A.18}$$

$$= \frac{1 - w(\theta_t) - s\frac{\kappa}{q(\theta_t)}}{\frac{\kappa}{q(\theta_t)}}. \tag{A.19}$$

Proof Equation A.19 follows directly from (A.17) and the assumptions.

How does this notion of payout ratio relate to the more traditional dividend-price ratio?

Lemma 5. *Consider the dividend-price ratio for the firm, D_t/P_t. Then,*

$$1 + \frac{D_t}{P_t} = \left(1 + \frac{D_t^l}{l_t}\right)\frac{N_t}{N_{t+1}} \tag{A.20}$$

Thus, if the labor market is in a steady state (defined as $N_t = N_{t+1}$), $D_t/P_t = D_t^l/l_t$.

Proof It follows from (2.10), the definition of dividends (2.7), and the law of motion for N_t (2.9) that

$$\begin{aligned} P_t + D_t &= l_t N_{t+1} + Z_t N_t - W_t N_t - \kappa_t V_t \\ &= (Z_t - W_t + l_t(1-s))N_t \end{aligned}$$

Thus

$$\begin{aligned} 1 + \frac{D_t}{P_t} &= \frac{P_t + D_t}{P_t} \\ &= \frac{Z_t - W_t + l_t(1-s)}{l_t}\frac{N_t}{N_{t+1}} \\ &= \left(1 + \frac{D_t^l}{l_t}\right)\frac{N_t}{N_{t+1}} \end{aligned}$$

where the last line follows from (A.18).

The following lemma gives a comparative static result on the price-dividend ratio. It is strictly applicable in the case of iid productivity growth (in our specification, constant disaster probability) because it relies on constant labor market tightness θ. When λ_t is constant, the economy converges deterministically to a steady state where θ is constant.

Lemma 6. *When the labor market is in a steady state ($\theta_{t+1} = \theta_t$), the price-dividend ratio is increasing in θ.*

Proof. It follows from (A.19) that

$$\frac{D_t^l}{l_t} = \frac{1 - w(\theta)}{\frac{\kappa}{q(\theta)}} - s$$

Because of (2.4), the first term is proportional to $(1 - w(\theta))\theta^{-\eta}$. It follows from (A.16) that $w(\theta)$ is increasing in θ (intuitively, wages are increasing in tightness). It is also necessary that $1 - w(\theta)$ is positive; otherwise, in this iid economy the firm would operate continually at a loss. Therefore $(1 - w(\theta))\theta^{-\eta}$ is decreasing in θ, and, by the second statement in Lemma 5, the price-dividend ratio is increasing in θ. □

A2.2. Constant Disaster Risk Model

Appendix A2.2.1 describes the compound Poisson process that is useful in the constant disaster risk case. Appendix A2.2.2 provides proofs for this case. When disaster risk is constant, labor market variables N_t, V_t and θ_t are deterministic. We assume that the economy has run for long enough that it has reached its steady state, with $N_t = N_{t+1}$, and similarly for V_t and θ_t.

A2.2.1. Compound Poisson Process

The algebraic rules for compound Poisson processes illustrated in this section are adapted from Cont and Tankov (2004). Drechsler and Yaron (2011) model jumps in expected growth and volatility using compound Poisson processes. Let $Q_{t,t+1}$ be a compound Poisson process with intensity $\tilde{\lambda}$. Specifically, $\tilde{\lambda}$ represents the expected number of jumps in the time period

$(t, t+1]$. Agents in the model view the jumps in $(t, t+1]$ as occurring at $t+1$. Then, $Q_{t,t+1}$ is given by

$$Q_{t,t+1} = \begin{cases} \sum_{i=1}^{\mathcal{N}_{t+1}-\mathcal{N}_t} \zeta_i & \text{if } \mathcal{N}_{t+1} - \mathcal{N}_t > 0 \\ 0 & \text{if } \mathcal{N}_{t+1} - \mathcal{N}_t = 0, \end{cases}$$

where $\mathcal{N}_t$ is a Poisson counting process and $\mathcal{N}_{t+1} - \mathcal{N}_t$ is the number of jumps in the time interval $(t, t+1]$. Jump size ζ is *iid*. We can take conditional expectations with $Q_{t,t+1}$ using

$$\mathbb{E}_t\left[e^{uQ_{t+1}}\right] = e^{\tilde{\lambda}\left(\mathbb{E}\left[e^{u\zeta}\right]-1\right)}, \tag{A.21}$$

where log of the right-hand side is the cumulant-generating function of $Q_{t,t+1}$. More precisely, the probability of observing k jumps over the course one period $(t, t+1]$ is equal to $e^{\tilde{\lambda}}\frac{\tilde{\lambda}^k}{k!}$. We take the t to be in units of months in our quantitative assessment of the model.

A2.2.2. Proof for the constant disaster risk case

We first prove the equation and comparative statics for the effective time discount factor.

Proof of Theorem 2 Consider the normalized value function in (2.25) and replace the disaster term with the compound Poisson process $Q_{t,t+1}$ with constant intensity $\tilde{\lambda}$:

$$j(\tilde{\lambda}, N_t) = \left[c_t^{1-\frac{1}{\psi}} + \beta\left(\mathbb{E}_t\left[e^{(1-\gamma)(\mu+\epsilon_{t+1}+Q_{t,t+1})} j(\tilde{\lambda}, N_{t+1})^{1-\gamma}\right]\right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}}\right]^{\frac{1}{1-\frac{1}{\psi}}}. \tag{A.22}$$

Conditional on time-t information, the realizations of ϵ_{t+1}, $Q_{t,t+1}$ and N_{t+1} are independent. Therefore, we can write (2.26) with

$$\hat{\beta}(\tilde{\lambda}) = \beta\mathbb{E}_t\left[e^{(1-\gamma)Q_{t,t+1}}\right]^{\frac{1-\frac{1}{\psi}}{1-\gamma}}. \tag{A.23}$$

Taking the expectation using the algebra introduced in Appendix A2.2.1, we compute the log of the effective time discount factor:

$$\log \hat{\beta}(\tilde{\lambda}) = \log \beta + \frac{1-\frac{1}{\psi}}{1-\gamma}\left(\mathbb{E}\left[e^{(1-\gamma)\zeta}\right]-1\right)\tilde{\lambda}. \tag{A.24}$$

Note that ζ takes only negative values. For $\gamma > 1$ and $\gamma < 1$ we have

$$\frac{\mathbb{E}\left[e^{(1-\gamma)\zeta}\right]-1}{1-\gamma} < 0. \tag{A.25}$$

Therefore, $\log \hat{\beta}(\tilde{\lambda})$ is decreasing in $\tilde{\lambda}$ if and only if $1-\frac{1}{\psi} > 0$ which is equivalent to $\psi > 1$.

Next we derive the equation for the riskfree rate:

Proof of Lemma 1 Because λ_t is constant and the economy is at its steady state, the stochastic discount factor (2.15) becomes:

$$M_{t+1} = \frac{\beta e^{-\frac{\mu}{\psi}-\gamma(\epsilon_{t+1}+Q_{t+1})}}{\mathbb{E}_t\left[e^{(1-\gamma)(\epsilon_{t+1}+Q_{t+1})}\right]^{\frac{\frac{1}{\psi}-\gamma}{1-\gamma}}}. \tag{A.26}$$

Here we have used (2.24) to substitute in for the value function. Taking the expectation in the denominator, the log stochastic discount factor becomes

$$\begin{aligned}\log M_{t+1} = \log \beta - \frac{\mu}{\psi} - \gamma(\epsilon_{t+1}+Q_{t+1})\\ -\frac{1}{2}\left(\frac{1}{\psi}-\gamma\right)(1-\gamma)\,\sigma_\epsilon^2 - \frac{\frac{1}{\psi}-\gamma}{1-\gamma}\left(\mathbb{E}\left[e^{(1-\gamma)\zeta}\right]\right)\tilde{\lambda}.\end{aligned} \tag{A.27}$$

It follows that the log risk-free rate $\log R_f = -\log \mathbb{E}[M_{t+1}]$ is given by:

$$\begin{aligned}\log R_f = -\log \beta + \frac{\mu}{\psi} + \frac{1}{2}\left(\frac{1}{\psi}-\frac{\gamma}{\psi}-\gamma\right)\sigma_\epsilon^2\\ +\left[\frac{\frac{1}{\psi}-\gamma}{1-\gamma}\left(\mathbb{E}\left[e^{(1-\gamma)\zeta}\right]-1\right)-\left(\mathbb{E}\left[e^{-\gamma\zeta}\right]-1\right)\right]\tilde{\lambda}.\end{aligned} \tag{A.28}$$

Note that the term $\frac{\frac{1}{\psi}-\gamma}{1-\gamma}$ is bounded above by $\gamma/(\gamma-1)$. The properties of the exponential implies $\frac{1}{\gamma}\mathbb{E}\left(\left[e^{-\gamma\zeta}\right]-1\right) > \frac{1}{\gamma-1}\mathbb{E}\left(\left[e^{-\gamma\zeta}\right]-1\right)$, which, together with the fact that ζ takes only negative values, implies that the risk-free rate is decreasing in disaster intensity (Tsai and Wachter (2015)).

The following Lemma recharacterizes the Euler equation in terms of model primitives:

Lemma 7. *The first-order conditions of the firm imply*

$$\hat{\beta}(\tilde{\lambda})e^{\mu\left(1-\frac{1}{\psi}\right)+\frac{1}{2}(1-\gamma)\left(1-\frac{1}{\psi}\right)\sigma_\epsilon^2}\left[\frac{1-w(\theta)+(1-s)\frac{\kappa}{q(\theta)}}{\frac{\kappa}{q(\theta)}}\right]=1, \tag{A.29}$$

where $w(\theta)$ is the wage normalized by productivity defined by (A.16) and $\hat{\beta}(\tilde{\lambda})$ is defined as in (A.23).

Proof We rewrite the Euler equation (A.10) in a more familiar form

$$E_t\left[M_{t+1}R_{t+1}\right]=1 \tag{A.30}$$

where we have divided through by l_t and used the characterization of returns in (2.11). The result follows from substituting (A.15) and (A.26) into (A.30) and solving the expectation using the definition of $\hat{\beta}(\tilde{\lambda})$ in (A.23).

Lemma 8. *The log expected equity return is given by*

$$\begin{aligned}\log\mathbb{E}_t\left[R_{t+1}\right]=&-\log(\beta)+\frac{\mu}{\psi}+\frac{1}{2}\left(\frac{1}{\psi}-\frac{\gamma}{\psi}+\gamma\right)\\&+\underbrace{\left(\mathbb{E}\left[e^{\zeta}\right]-1\right)}_{\textit{Productivity growth}}\tilde{\lambda}\\&-\underbrace{\left(\frac{1-\frac{1}{\psi}}{1-\gamma}\left(\mathbb{E}\left[e^{(1-\gamma)\zeta}\right]-1\right)\right)}_{\textit{Labor market}}\tilde{\lambda}.\end{aligned} \tag{A.31}$$

Proof. (A.29) implies

$$\frac{1 - w(\theta) + (1-s)\frac{\kappa}{q(\theta)}}{\frac{\kappa}{q(\theta)}} = \frac{1}{\hat{\beta}(\tilde{\lambda})e^{\mu\left(1-\frac{1}{\psi}\right)+\frac{1}{2}(1-\gamma)\left(1-\frac{1}{\psi}\right)\sigma_\epsilon^2}}. \tag{A.32}$$

Therefore, by (A.15)

$$R_{t+1} = \frac{e^{\mu+\epsilon_{t+1}+Q_{t+1}}}{\hat{\beta}(\tilde{\lambda})e^{\mu\left(1-\frac{1}{\psi}\right)+\frac{1}{2}(1-\gamma)\left(1-\frac{1}{\psi}\right)\sigma_\epsilon^2}}, \tag{A.33}$$

Equation (A.31) follows from taking the expectation of (A.33) using rules introduced in Section A2.2.1. □

Lemma 2 follows from (A.31) and the equation for the riskfree rate given in (A.28). Corollary 2 follows from inspection of the terms multiplying $\tilde{\lambda}$ in (A.31).

Finally we establish comparative statics for the price-dividend ratio.

Proof of Theorem 3 It follows from Lemma 7 (Equation A.29) that

$$-\log\left(1 - s + \frac{1-w(\theta)}{\kappa}\xi\theta^{-\eta}\right) = \log\hat{\beta}(\tilde{\lambda}) + \mu\left(1-\frac{1}{\psi}\right) + \frac{1}{2}(1-\gamma)\left(1-\frac{1}{\psi}\right)\sigma_\epsilon^2, \tag{A.34}$$

where, from Theorem 2

$$\log\hat{\beta}(\tilde{\lambda}) = \log\beta + \frac{1-\frac{1}{\psi}}{1-\gamma}\left(\mathbb{E}\left[e^{(1-\gamma)\zeta}\right]-1\right)\tilde{\lambda}.$$

Define

$$h(\tilde{\lambda}) \equiv -\log\left(1 + \frac{D_t^l}{l_t}\right) = -\log\left(1 + \frac{D_t}{P_t}\right) \tag{A.35}$$

The second equality follows from Lemma 5. The result then follows from adding 1 to (A.19) and taking the negative of the log, then substituting the result into the left hand side of (A.34).

A2.3. Equilibrium Solution

Let x' denote the value of the variable x in period $t+1$ and x the value at t. We can rewrite the normalized value function (2.25) as

$$g(\lambda, N) = j(\lambda, N)^{1-\frac{1}{\psi}}. \tag{A.36}$$

The value function and policy functions are functions of the exogenous state variable λ and the endogenous state variable N. The dynamics of the stochastic discount factor and returns are driven by four shocks: disaster probability λ', normal times productivity shock ϵ', disaster indicator d' and disaster size ζ'. Let $\mathbb{E}$ be the expectation operator over four shocks. In our numerical procedure, we solve for the consumption policy $c(\lambda, N)$ and the value function $g(\lambda, N)$. The market clearing condition allows us to compute the vacancy rate given the consumption policy.

It follows from (2.15) and (2.24) that the stochastic discount factor can be written as

$$\begin{aligned} M(\lambda, N; \lambda', \epsilon', d', \zeta') =& \beta e^{-\frac{\mu}{\psi}+\frac{1}{2}(1-\gamma)\left(\gamma-\frac{1}{\psi}\right)\sigma_\epsilon^2} e^{-\gamma(\epsilon'+d'\zeta')} \\ & \cdot \mathbb{E}\left[e^{(1-\gamma)d'\zeta'} g(\lambda', N')^{\frac{1-\gamma}{1-\frac{1}{\psi}}}\right]^{\frac{\gamma-\frac{1}{\psi}}{1-\gamma}} \left(\frac{c(\lambda', N')}{c(\lambda, N)}\right)^{-\frac{1}{\psi}} g(\lambda', N')^{\frac{\frac{1}{\psi}-\gamma}{1-\frac{1}{\psi}}}. \end{aligned} \tag{A.37}$$

The equity return is given by

$$R(\lambda, N; \lambda', \epsilon', d', \zeta') = e^{\mu+\epsilon'+d'\zeta'} \left[\frac{1 - w(\lambda', N') + (1-s)\frac{\kappa}{q(\theta(\lambda', N'))}}{\frac{\kappa}{q(\theta(\lambda, N))}}\right], \tag{A.38}$$

where

$$w(\lambda, N) = (1-B)b + B(1 + \kappa((1-\nu)\bar{\theta} + \nu\theta(\lambda, N))) \tag{A.39}$$

and

$$\theta(\lambda, N) = \frac{N + b(1-N) - c(\lambda, N)}{\kappa(1-N)}, \tag{A.40}$$

which follows from (2.21).

The equilibrium conditions that $c(\lambda, N)$ and $g(\lambda, N)$ have to satisfy are

$$\mathbb{E}\left[M(\lambda, N; \lambda', \epsilon', d', \zeta')R(\lambda, N; \lambda', \epsilon', d', \zeta')\right] = 1 \tag{A.41}$$

and

$$g(N, \lambda) = c(N, \lambda)^{1-\frac{1}{\psi}} + \beta e^{\left(1-\frac{1}{\psi}\right)\mu + \frac{1}{2}\left(1-\frac{1}{\psi}\right)(1-\gamma)\sigma_\epsilon^2} \left(\mathbb{E}\left[e^{(1-\gamma)d'\zeta'} g(\lambda', N')^{\frac{1-\frac{1}{\psi}}{1-\gamma}}\right]\right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}}. \tag{A.42}$$

We approximate the AR(1) process for log disaster probability by a 12-state Markov process and use the corresponding probability transition matrix to calculate expectations over λ'. The expectations over ζ' and ϵ' can be taken directly since their distributions are *iid*.

We approximate the policy function and the value function by a polynomial of employment level N where the polynomial coefficients are estimated for each value of the disaster probability separately. We use $n+1$ nodes for employment to conduct the approximation by an n'th order polynomial. As a result we have $24(n+1)$ unknowns and equations resulting from the equilibrium conditions (A.41) and (A.42). We evaluate the equilibrium conditions at the nodes of the Chebyshev polynomial of order n. Our quantitative results are not significantly different for polynomial approximations of order 3 or higher.

A2.4. Data Sources

We use data from 1951 to 2013 for all variables.

- Z is the seasonally adjusted quarterly real average output per hour in the nonfarm business sector, constructed by the Bureau of Labor Statistics (BLS) from National Income and Product Accounts (NIPA) and the Current Employment Statistics (CES). Output per person yields nearly indistinguishable results.

- P is the real price of the S&P composite stock price index, downloaded from Robert Shiller's website (www.econ.yale.edu/ shiller/data.htm).

- P/E is the cyclically adjusted price-earnings ratio, downloaded from Robert Shiller's website (www.econ.yale.edu/ shiller/data.htm).

- P/Z is the price-productivity ratio scaled to have the same value as P/E in the first quarter of 1951.

- U is the seasonally adjusted unemployment, constructed by the BLS from the Current Population Survey (CPS). Quarterly values are calculated averaging monthly data.

- V is the help-wanted advertising index constructed by the Conference Board until June 2006. We use data on vacancy openings from Job Openings and Labor Turnover Survey (JOLTS) from 2000 to 2013. We extrapolate the help-advertising index until 2013 and observe that our extrapolation has a correlation of 0.96 in the period from 2000 to 2006 where both data sources are available. Quarterly values are calculated averaging monthly data.

- W denotes wages measured as the product of labor productivity Z and labor share from the BLS.

- C is annual real personal consumption expenditures per capita from the BEA.

- Y is annual real gross domestic product (GDP) per capita from the BEA.

- R is the value weighted return market index return including distributions from CRSP. Real returns are calculated using inflation rate data from CRSP. Net returns are multiplied by 0.68 to adjust for financial leverage.

- R_b is the 1-month Treasury bill rate from CRSP. Real rates are calculated using inflation rate data from CRSP.

- Δc and Δy denote log consumption and log output growth. Annual growth rates from monthly simulations that we compare to data values are calculated aggregating consumption and output levels over every year. Let $C_{t,h}$ denote the consumption level in year t and month h. Annual log consumption growth in the model is calculated as

$$\Delta c_{t+1} = \log\left(\frac{\sum_{i=1}^{12} C_{t+1,i}}{\sum_{i=1}^{12} C_{t,i}}\right). \tag{A.43}$$

The same method is applied to output growth as well.

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